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Authorship

This thesis consists of three individual papers, two of which are co-authored. In the jointly-written papers, each author contributed significantly to the completion of the work. Chapter 2 represents a collaboration with Dr. André Lorentz (BETA, Université de Strasbourg, France). In this paper, agent-based modeling and simulation were employed with Dr. Lorentz contributing significantly to the development phase of the model. Chapter 3 is a single-authored paper, while Chapter 4 constitutes a collaboration with Professor Uwe Cantner who provided indispensable support at different stages of the research from the conceptualization, questionnaire preparation and analysis to the proof-reading of the manuscript.

Dedications

to Tisha, Ayyash, Shazia, Ibu, Bapak, Mamah, and Mpah.

Your continuous prayers, supports, and patience give me strength to keep going in this journey.

Are those who know and those who do not know alike? Only the men of understanding are mindful.

(Surah Al Zumar 39:9)

Zusammenfassung

Untersuchung des Einflusses von Netzwerkeffekten auf disruptive Technologien im sozialen Netzwerken

Das Hauptthema meiner Dissertation beinhaltet drei Untersuchungsgebiete: Disruptive Technologien, Netzwerkeffekte und soziale Netzwerke. Durch die jüngsten Fortschritte der Computertechnologie, der Mobiltelefonie und des Internets wird technologische Disruption ein ständig auftretendes Phänomen. Etablierte Technologien und dominante Firmen in verschiedenen Industrien sehen sich beständig der Gefahr ausgesetzt, von neuen Technologien und Wettbewerbern verdrängt zu werden.

Die Theorie disruptiver Technologien, welche 1997 von Clayton Christensen vorgetragen wurde, erfuhr große Aufmerksamkeit von Managementforschern und Manager. Govindarajan und Kopalle (2006) unterstützten die Theorie und schlugen das "technology disruptiveness measurement" vor, welches postuliert, dass eine disruptive Innovation (1) unterlegen in den Attributen sein sollte, die dem Durchschnittskonsumenten wichtig sind, (2) neue Vorteile bereitstellen sollte, um neue Konsumentengruppen oder den preisempfindlichen Durchschnittskonsumenten zu erreichen, (3) zu einem geringeren Preis verkauft werden sollte und (4) zunächst in einer Nische und dann im Gesamtmarkt erfolgreich sein sollte.

Diese Theorie, welche später in disruptive Innovation (Christensen und Raynor, 2003) umbenannt wurde, um nicht nur Technologie im engeren Sinne, sondern auch andere Disruptionen wie Dienstleistungen und Geschäftsmodelle zu umfassen, hat sowohl Unterstützung als Kritik erfahren, und zwar von theoretischer sowie von empirischer Seite. Sood und Tellis (2011), Beispielsweise, argumentierten auf Basis ihrer empirischen Ergebnisse, dass die Bedeutung disruptiver Technologien überbewertet wird. Sie zeigten, dass, über den Verlauf von 50 Jahren, nur wenige der Technologien, welche als potentiell disruptiv identifiziert wurden, sich als tatsächlich disruptiv herausstellten. Vaishnav (2008) zeigte als Beispiel drei verschiedene Technologien, welche als potentiell disruptiv bezeichnet wurden. Jedoch verursachte nur eine der dreien größere Änderungen in der Industrie. Diese Dissertation versucht diese Probleme anzusprechen, indem Netzwerkeffekte und die Netzwerkstruktur der Konsumenten bei Betrachtung der Mechanismen disruptiver Technologien beachtet werden.

Der Grundgedanke dieser Arbeit ist, dass die ursprüngliche Theorie der disruptiven Innovation eine Beachtung der Netzwerkeffekte und der Einbettung der

Konsumenten in Gemeinschaften und die Gesellschaft vermissen lässt. Moderne Technologien zeichnen sich jedoch durch Netzwerkeffekte oder Netzwerkexternalitäten aus, wodurch der Nutzen, den ein Konsument aus einer Technologie ziehen kann, sich mit der Anzahl der Adaptoren erhöht (Arthur, 1989; Keller und Hüsig, 2009; Vaishnav, 2008). Zudem haben viele Studien betreffend der Diffusion von Innovationen gezeigt, dass die Adaptionsentscheidung eines Konsumenten von wichtigen anderen Menschen beeinflusst wird, die mit ihm oder ihr verbunden sind (Delre et al., 2007, 2010; Janssen und Jager, 2004; Lee et al., 2006; Lee und Song, 2003). Daher ist es das "kühne Ziel" dieser Arbeit, eine alternative Sichtweise auf disruptive Technologien anzubieten, die Netzwerkeffekte und die Dynamik technologischer Konkurrenz in komplexen Netzwerken berücksichtigt und dadurch (zumindest bis zu einem bestimmten Punkt) einige verwirrende oder sogar widersprüchliche Ansichten in der Literatur bezüglich disruptiver Technologien oder Innovationen aufzuklären hilft.

Diese Dissertation, welche aus drei Artikeln besteht, versucht Licht auf die Frage zu werfen, wie Netzwerkeffekte die Chance auf Disruption beeinflussen, unter genauer Untersuchung der Mechanismen von disruptiver Technologie in komplexen Netzwerken. Der erste Artikel analysiert, unter Verwendung von Agenten-basierter Modellierung und Simulationen, die Dynamik technologischer Konkurrenz als Zusammenspiel von Firmen und Konsumenten in einem Markt mit heterogenen Konsumenten. Abhängig von der Stärke der Netzwerkeffekte, kommt der Heterogenität der Konsumentenpräferenzen eine wichtige Rolle bei der Entscheidung des Wettbewerbs der Firmen zu. Der zweite Artikel, welches eine Erweiterung des Ersten Artikels durch die Aufgabe der starken Annahme eines vollständigen Netzwerks ist, bietet theoretische Einsichten darüber wie verschiedene Netzwerkstrukturen der Konsumenten das Ergebnis des Wettbewerbs beeinflussen. Der dritte Artikel, welche die Stufe der Theorie verlässt und eine empirische Analyse bietet, untersucht die Determinanten der Akzeptanz disruptiver Technologien, welche Netzwerkexternalitäten aufweisen, in Deutschland und Indonesien. Dieser länderübergreifende Vergleich repräsentiert nicht nur den Unterschied zwischen entwickelten Staaten und Entwicklungsländern, sondern hebt auch den Unterschied zwischen einer individualistischen und einer kollektivistischen Gesellschaft (aus soziologischer Perspektive) und den Unterschied starker oder schwacher Konnektivität (aus Sicht der Analyse sozialer Netzwerke) hervor.

Die beiden nachfolgenden Paragraphen sind dem Abstract des ersten Artikels entnommen: Die Theorie disruptiver Technologien erhält viel Aufmerksamkeit und hat starken Einfluss auf Forscher und Manager, welche sich mit technologischem Wettbewerb beschäftigen. Einige Studien formalisieren die disruptive Technologie, um die Mechanismen und Determinanten der Disruption zu erklären (Adner 2002; Adner und Zemsky, 2005; Buchta et al., 2004; Mount, 2012; Vaishnav, 2008). Während einige moderne Technologien als disruptiv erkannt werden, zeichnen sie sich auch durch steigende Grenzerträge der Adaption oder Netzwerkeffekte aus

(Keller und Hüsig, 2009; Vaishnav, 2008). Jedoch hat die Frage wie die Netzwerkeffekte den Mechanismus der Disruption beeinflussen bisher wenig Aufmerksamkeit in formalen Modellen bezüglich disruptiver Technologien gefunden. Daher entwickeln wir in dieser Studie ein formales Modell, um die Dynamik der Disruption zu untersuchen. Hierfür untersuchen wir die Verbindung zwischen technologischer Entwicklung, Konsumenten- und Firmenentscheidungen und der Nachfragestruktur unter Einfluss verschieden starker Netzwerkeffekte. Das Modell wird mit Hilfe Agentenbasierter Software des „Laboratory for Simulation Development“ (Lsd) simuliert.

Die Ergebnisse deuten darauf hin, dass schwache Netzwerkeffekte verschiedene Wettbewerbsergebnisse erzeugen können, zum Beispiel wettbewerbliche Isolation, Konvergenz und Disruption. Die Heterogenität der Konsumentenpräferenzen hat einen Einfluss auf das Ergebnisse des Wettbewerbs. Im Gegensatz dazu führen starke Netzwerkeffekte immer zu “winner-takes-all” Situationen, unabhängig von den Präferenzen der Konsumenten.

Die drei folgenden Paragraphen sind dem zweiten Artikel entnommen: Obwohl die Forschung der Nachfrageseite zunehmend mehr Aufmerksamkeit schenkt (Adner 2002; Adner und Zemsky, 2005; Malerba et al., 2007), fehlt die Diskussion über disruptive Innovationen in komplexen Netzwerken fast völlig. Dieser Artikel konzeptioniert den technologischen Wettbewerb und die Wahrscheinlichkeit disruptiver Innovation unter der Annahme, dass die Adaptionsentscheidungen der Konsumenten von ihnen nahe stehenden Personen, z.B. Familienmitglieder, Freunde und Kollegen, abhängen und das die Konsumenten über ein Netzwerk mit bestimmter Topologie verbunden sind. Aufbauend auf früheren Studien bezüglich technologischen Wettbewerbs, inkompatibelen Markteintritts und wettbewerblicher Diffusion, sowie umfangreicher Literatur über komplexe Netzwerke und die Analyse sozialer Netzwerke, bietet diese Studie einen Rahmen zur Untersuchung des Wettbewerbs und disruptiver Innovationen unter der Annahme verschiedener Netzwerkstrukturen der Konsumenten untereinander.

Ausgehend von diesen theoretischen Überlegungen können folgende Mutmaßungen getroffen werden: Ein Markt, welcher von hohem Clustering und einer starken Separation geprägt ist, sowie eine Nische mit hoher Vernetzung der Akteure bereithält, erlaubt es einer disruptiven Technologie auch dann zu überleben, wenn starke Netzwerkeffekte vorhanden sind. Sobald die potentiell disruptive Technologie in der Nische Fuß gefasst hat, sollten Neueinsteiger oder etablierte Firmen Verbindungen zu Akteuren außerhalb der Nische suchen, um die Informationen weiter zu verbreiten und die Diffusion zu koordinieren (Witt, 1997), um so Zugang zum Hauptsegment des Marktes zu erhalten. Andernfalls wird die Technologie in ihrer Nische verbleiben. Die erfolgreichen Versuche der Kontaktaufnahme außerhalb der Nische, verbunden mit andauernden Verbesserungen der Technologie, welche sie der etablierten Technologie überlegen macht, erlauben das erreichen einer kritischen Masse und erhöhen daher die Wahrscheinlichkeit der Disruption.

Dieser Ansatz könnte auch für die Diskussion bezüglich des Überwindens von Lock-In Situationen interessant sein (Cantner und Vanuccini, 2016; Malerba et al., 2007; Witt, 1997). Ausgehend von der Perspektive komplexer Netzwerke, sind wir möglicherweise in der Lage die Auffassung des unentrinnbaren Lock-Ins anzugreifen, indem wir ein Verständnis entwickeln, unter welchen Umständen eine potentiell disruptive Technologie sich zunächst in einer Nische durchsetzen kann, dann über diese hinaus wächst und eine kritische Masse formt, mit welcher sie möglicherweise den gesamten Markt „angreifen“ kann.

Der folgende Absatz ist dem dritten Artikel entnommen: Unser Forschungsbeitrag versucht Licht auf die Frage zu werfen, wie die disruptivität eine Technologie und Netzwerkeffekte die Akzeptanz der Konsumenten bezüglich neuer Technologien beeinflusst. Wir haben 480 Antworten bezüglich der Akzeptanz neuer Technologien durch die Konsumenten in Deutschland und Indonesien gesammelt, betreffend drei verschiedene Technologien: Festnetztelefonie, Internet-Telefonie (z.B. Skype) und Messaging-Diensten (z.B. WhatsApp). Unsere abhängige Variable ist die Differenz in der Nutzung der einzelnen Technologien. Wir entwickeln ein Modell auf Basis der „Theory of Planned Behaviour“, des „Technology Acceptance Model“ und verschiedener Variablen mit Bezug zum Netzwerkeffekt. Wir führen paarweise Vergleiche durch: Festnetztelefonie vs. Internet-Telefonie, Messaging-Diensten vs. Festnetztelefonie und Messaging-Diensten vs. Internet-Telefonie. Daher erhalten wir drei Fälle, für die wir multiple Regressionen durchführen.

Wir finden einen positiven und signifikanten Zusammenhang zwischen die Differenz in „Perceived usefulness“ und die Differenz in „Attitude towards using“, anschließen einen positiven und signifikanten Zusammenhang zwischen die Differenz in „Attitude towards using“ und die Differenz in „Intention to use“; daher der positive Effekt von die Differenz in „Perceived usefulness“ auf die Differenz in „Intention to use“ durch die Differenz in „Attitude towards using“ mediiert wird. Darüber hinaus zeigt sich, dass die Differenz in „Subjective norms“ den positiven Zusammenhang zwischen die Differenz in „Perceived current and future number of users“ und die Differenz in „Intention to use“ mediiert. Ein solcher mediierende Effekt zeigt sich allerdings nicht für die Differenz in „Perceived behavioral control“. Ferner finden wir einen positiven und signifikanten Zusammenhang zwischen die Differenz in „Intention to use“ und die Differenz in „Actual use“. Im Hinblick auf länderspezifische Einflussfaktoren machen unsere Ergebnisse deutlich, dass in Deutschland, trotz der Verfügbarkeit von Internet-Telefonie und Messaging-Diensten, die meisten Ferngespräche nach wie vor mittels Festnetztelefonie getätigt werden.

1 Introduction

The domain of technological change is dominated by the view that displacement of established technologies and incumbent companies is driven by the superior performance of new technologies introduced by entrants to the field (Dosi, 1982; Foster, 1986; Tushman and Anderson, 1986). However, Christensen (1997) put forward the prospect of technologies with inferior performance displacing more established ones by pioneering the concept of disruptive technology.

With the recent advances in digital technology, mobile technology and the internet, technology disruption has become a more common phenomenon (Capgemini, 2015; Global Centre for Digital Business Transformation, 2015). Established technologies and companies operating in various industries are continually under threat of disruption by new technologies and entrants to the field. As a case in point, WhatsApp disrupted the then existing global text messaging market worth USD100 billion (The Economist, 2015). In the course of its development, WhatsApp also allowed users to make mobile voice calls.

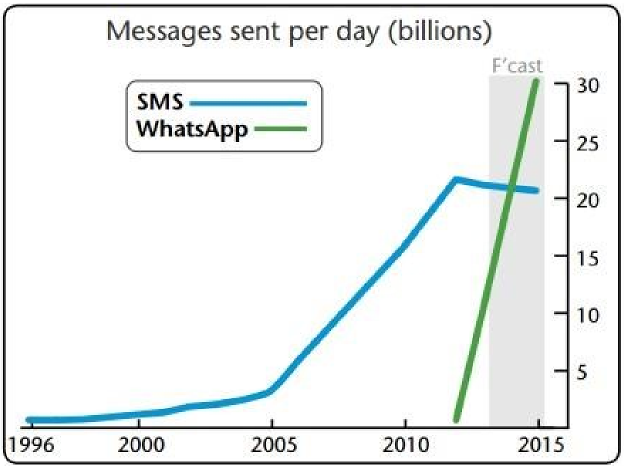

Figure 1.1 How WhatsApp disrupted short-messaging-service industry
(Sources: Portio Research, a16z, The Economist, 2015)

1.1 Overview of the problems related to disruptive technologies theory

Disruptive technology theory, first propounded by Clayton Christensen in 1997, has attracted considerable attention from management scholars and practitioners, receiving as much theoretical and empirical support as criticism (Danneels, 2004, Markides, 2006, Sood and Tellis, 2011). However, a number of critics have argued that Christensen cherry-picked disruption cases as a means of supporting his theory. Indeed, Sood and Tellis (2011) considered it to be over-exaggerated. Their own empirical research strongly suggestedThat, across a period of 50 years and a sample of 36 technologies, the technology disruption caused by entrants introducing novel and potentially disruptive technologies amounted to only eight percent.

The basic tenet of the thesis presented here is that the original theory of disruptive technology lacks sufficient consideration of network effects and the nature of consumer inter-connectivity, both within a specific community and society more generally. Modern technologies are characterized by network effects through which consumers derive greater benefit as the number of adopters increases (Keller and Hüsig, 2009; Vaishnav, 2008). Moreover, many studies of innovation diffusion have revealed that an individual consumer's adoption decision is affected by significant others connected to that individual (Delre et al., 2007, 2010; Janssen and Jager, 2004; Lee et al, 2006; Lee and Song, 2003). Hence, it is necessary to include network effects and consumer network structures in any discourse on technology disruption

The ambitious objective of this thesis is that of providing an alternative, demand-focused view of disruptive technology by incorporating network effects and the dynamics of technology competition in social networks in order to clarify various confusing or even contradictory views in the literature on the subject. This involves elucidating how network effects and consumer network structures influence the probability of technology disruption. Moreover, the empirical exercises contained in this work provide the determinants of user acceptance of disruptive technology within network effects in Germany and Indonesia.

This study rests its theoretical basis on three core familiar theories, i.e. disruptive technology, network effects and social networks.

1.2 Disruptive technology

Disruptive technology theory was advanced by Christensen in his renowned book of 1997 entitled "The Innovator's Dilemma". In this work, he explained how incumbent firms, despite applying best practice in terms of taking feedback on consumers' needs into account, fail to cope with new entrants offering innovative disruptive technology. According to Christensen, it is disruptive technologies, promoting different values to mainstream technologies and initially inferior to the latter in terms of performance, that are of greatest importance to mainstream customers. Christensen introduced the concept of evolving performance over time, while also plotting the trajectories of the product performance of different technologies provided by companies and demanded by customers within various market segments. He showed that technology disruption occurs when these trajectories intersect.

Each disruptive technology-based product is capable, in its early stages, of only serving a niche segment. Further development can, however, raise the performance of disruptive technology to a level sufficient to satisfy mainstream customers. Despite having been improved, the performance of disruptive technology remains inferior to that of the established mainstream variety which is also developing. Over time, due to an improvement rate more rapid than the market can accommodate, mainstream technology performance may, ultimately, exceed the demand from mainstream customers, resulting in performance oversupply. Market disruption occurs when a new disruptive technology product displaces a mainstream product in the mainstream market enabled by mainstream technology performance oversupply and resulting from the lower price of the new technology (Adner, 2002; Yu and Hang, 2009).

A heated debate has developed regarding the definition and scope of disruptive technology (Yu and Hang, 2009) with some scholars supporting Christensen's theory of disruptive technology, while others propose their own somewhat different viewpoint. Others have criticized the vagueness of the concept as well as its predictive potential (Danneels, 2004; Markides, 2006). Govindarajan and Kopalle (2006), contributors of a series of analyses of the disruptiveness scale's reliability and validity, suggested that disruptive innovation should (1) be inferior to the attributes that mainstream customers value, (2) offer innovative value propositions to attract a new customer segment or a more price-sensitive mainstream market, (3) be sold at a lower price, and (4) penetrate the market from niche to mainstream.

As the disruptive innovation mechanism is of particular interest, Christensen (1997) argued that two conditions drive a new technology or innovation from a low-end niche segment to eventually displace established technology in the market's mainstream segment. Firstly, the continuous improvement of innovative technology over time eventually makes it more attractive to mainstream segment consumers, although it is the low-end of that segment which demonstrates greater sensitivity to price. Secondly, performance oversupply of established technology, which refers to performance improvements beyond consumer requirements, yields a diminishing marginal utility for consumers within the mainstream segment (Adner, 2002; Christensen, 1997). This "diminishing marginal utility translates into decreasing willingness to pay" (Adner, 2002) and makes the lower price of the disruptive technology offered more attractive.

1.3 Network effects

When two or more technologies compete, the increasing return on adoption promotes positive feedback, i.e. a higher rate of adoption renders the technologies more familiar to users and promotes further improvement (Arthur, 1989). This, in turn, induces the users to adopt a wider range of technologies and eventually engender customer lock-in. When two or more technologies compete for a market of potential adopters, an ‘insignificant event’ might favor one over the other, prompting it to achieve sufficient adoption and eventually dominate the market, resulting in a winner-takes-all outcome. Arthur (1989) provided a dynamic model demonstrating how an insignificant or random historical event influences the selection, the market outcome being multiple equilibria. Lock-in might result in an inefficiency problem in that the dominance of inefficient technology prevents a new and superior variety entering the market.

Arthur (1989) suggested that potential users value a product or technology for two reasons; their intrinsic preferences and the number of existing consumers. In other words, intrinsic preference and the degree of take-up determine the utility of a technology for those who adopt it. Arthur is specifically interested in the increasing returns on adoption where the utility of a particular technology for a new user increases with the number of those previously having adopted it. Such network effects resulting from an increasing return on adoption suggest a winner-takes-all situation and lock-in to be the inevitable consequences. This notion of has generated heated debate among economists (Cantner and Vannuccini, 2016; Leydesdorff, 2000; Shurmer, 1993; Witt, (1997)), some of whom conducted theoretical and empirical studies challenging the notion of inescapable lock-in.

Srinivasan, et al. (2004) posited an important concept about the nature of network effects, asserting that these are not dichotomous, i.e., present or absent, but, rather, exist in varying degrees. In the course of their empirical investigation of the impact of network externalities on pioneer survival, these researchers employed different groups of raters composed of academic experts and managers to measure the direct and indirect network effects of over forty product technologies. They investigated both those with low network effects, such as electric toothbrushes and pocket calculators, as well as ones with very high network effects, for instance, fax machines and operating systems for personal computers. Srinivasan et al. related the different degrees of such technologies’ network effects to the survival of “pioneers” which they defined as companies first introducing the corresponding technology.

Theoretically, there are two ways in which network effects might influence one’s acceptance of a certain technology. An individual’s acceptance or rejection of a technology is influenced by: (1) his/her social relationship with other users, i.e. the social influence, and (2) the total number of users of that technology within the market, known as the installed base (Pontiggia and Virili, 2009). Social influence refers to the pressure exerted by other people or groups that affect a user’s decision to accept or reject a particular technology, while the total number of users in the market influences an individual to accept a technology due to the perceived benefit of adopting one with a large, established base.

1.4 Social networks, diffusion of innovation and technology competition

1.4.1 Social networks

Networks are modeled by graphs consisting of nodes and edges or links. Graphs can be categorized into: (1) complete graphs and (2) sparse graphs. A complete or fully-connected graph exists when every node of a network is connected to every other node. Technically speaking, this graph features one degree of separation or a path length of one. When an individual consumer connects with a smaller number of counterparts, a sparse graph might constitute a more appropriate representation. Several ways of characterizing a sparse graph include; regular, random, small-world and scale-free (Watts and Strogatz, 1998; Barabasi and Albert, 1999; Amaral et al., 2000). Regular and random graphs can be classified as simple networks, whereas small-world and scale-free graphs are categorized as complex in nature.

Simple networks consist of two different network topologies; regular and random. The regular variety features a simple network coupled in geometrically consistent ways where "many phenomena exhibit spatial order by obeying the rule of local, nearest neighbor interactions" (Lee, et al., 2006). This graph exhibits the property of a high degree of clustering, meaning that individuals within the network share a substantial number of common acquaintances. The other characteristic of a regular graph is long path length or a high degree of separation since the structure tends to increase the number of steps necessary for one individual to connect with any other individual within the network. Random networks represent another simple network topology where any individual can be connected to any other individual in the world. The role of physical distance is irrelevant to random networks and, given the presence of such random connectivity, it requires only a few steps for each member to reach every other member (Erdös and Rényi, 1959). In other words, the network is characterized by a low degree of separation or short path length. The other characteristic of random networks is that of a low degree of clustering where each individual is unlikely to share common acquaintances since he/she randomly contacts strangers. Internet chat rooms may well belong to this network.

Watts and Strogatz (1998) put forth an idea on how to deal with the complexity of a real network structure. The basic premise is that the complex network in this world lies somewhere between regular and random networks. Lee et al. (2006) highlighted three advantages of using this topology: (1) no constraints of physical distance on social interaction exist (2) the model proposed by Watts and Strogatz (WS) allows researchers to examine the dynamics of complex networks by adjusting only one parameter, namely; the availability of shortcuts or re-wiring probabilities (β) and (3) this WS model represents the features of real world networks: high clustering and low degrees of separation. Large networks, such as the world-wide-web and scientific collaborations, have been analyzed and node connectivity has been found to follow a scale-free power-law distribution (Barabási and Albert, 1999). The generation of this scale-free graph, according to these researchers involves: (1) networks expanding over time through the addition of new nodes and (2) new nodes preferring to be connected with existing ones already enjoying numerous connections (hubs). This phenomenon is often referred to as preferential attachment.

1.4.2 Diffusion of innovation and technology competition in social networks

An overview of the literature on the diffusion of innovation within social networks has been conducted in order to understand the reasons an innovative technology being more efficiently diffused in certain network structures . Understanding the underlying reasons will, hopefully, enable them to be related to the context of technology competition and the probability of disruption.

Firstly, a brief review of the diffusion of single innovations within social networks is presented. Some notable works on this subject include those of Abrahamson and Rosenkopf (1997), Delre et al. (2006 and 2010) and Janssen and Jager (2003) in which agent-based modeling and computer simulation are widely employed. From the literature on innovation diffusion, the manner in which a network's structure influences its speed and pattern can be understood. Abrahamson and Rosenkopf (1997) proposed that the number of network links and their structural idiosyncrasies can greatly affect the extent of innovation diffusion among members of a social network. Delre et al. (2006) demonstrated how the degree of randomness within the network influences the rate of diffusion. The latter is low in regular networks, increases in small-world networks but, again, appears low in random networks. Recent research has demonstrated that large networks are characterized by scale-free, power-law distribution. Janssen and Jager (2003) investigated the role of hubs, small groups of consumers with numerous connections, on resulting market dynamics. Their simulation results showed that hubs exert significant influence on the consumption behavior of others. Delre et al. (2010) investigated the role and effects of hubs on innovation diffusion, concluding that these can vary in different markets. Although hubs are acknowledged as having a great impact on many consumers, simulation results confirm that when their maximum number of connections is limited, innovation diffusion is severely hindered and the outcome uncertain.

A number of works on the dynamics of technology competition within social networks have been reviewed. Studies of how consumer network structures play a role in the competition between technologies, particularly the role of a network structure in the entry of an innovative and incompatible technology when an existing one was established or dominated the market (lock-in), appear in the literature (Janssen and Jager, 2001; Janssen and Jager, 2003; Lee et al., 2003; Lee and Song, 2005). The common conclusion of such studies highlights the importance of consumer network structures in market dynamics or competitive outcomes. In investigating incompatible entry into small-world networks, Lee and Song (2005) emphasized that the longer the degree of separation of consumer network structures, the more probable incompatible entry becomes. This suggests that small-world networks with numerous shortcuts and random networks are unfavorable to new, incompatible technology. Janssen and Jager (2001 and 2004) explained how different network structures, i.e. small-world and scale-free networks, together with psychological needs exert an important influence on market dynamics. They argued that hubs, people with numerous contacts characterizing scale-free networks, exert considerable influence on the behaviour of other consumers. Reich (2015) highlighted the influence of network structures on the diffusion of new technology where individuals can enter into discussions, coordinate opinions and make joint decisions. Hence, the degree of connectedness or 'cohesiveness' is of considerable significance. It is assumed that 'cohesiveness' within this context is identical to the concept of clustering. In other words, the more 'cohesive' the community, the higher the degree of clustering within the network. Reich suggests that a cohesive community enjoys a specific trade-off. On the one hand, it hinders diffusion by preventing the importation of new technology into the group but, on the other, when group members are in a position to act collectively in adopting technology, this 'cohesiveness' enables innovation to diffuse effectively. Reich concluded that where innovative technology with a high degree of network effects or externalities requires a higher number of adopters before other potential adopters are willing to follow suit, cohesive groups facilitate diffusion.

1.5 Investigating the influence of network effects on the mechanism of technological disruption within social networks

The main purpose of this doctoral thesis is to investigate the probability of technological disruption when network effects are present. It also investigates how consumer network structures, the social networks connecting consumers to each other, influence the potential for such disruption.

The foregoing theoretical overview of disruptive technology, network effects and social networks provides the building blocks for the core proposition of this thesis. Disruptive technology theory implies the existence of technology competition where a novel variety with certain characteristics might eventually displace an established one. Extensive literature exists containing analyses of the supply side, i.e. established firms undergoing development and the manner in which they should respond to disruptive threats, as well as those involved in developing potentially disruptive technology and how they should launch disruptive strategies. However, the still limited demand perspective of the theory is identified. This is particularly the case for technologies characterized by network effects where user benefit derived from the technology is higher as the number of adopters increases. The different degree of network effects influences the probability of new, potentially disruptive technology undermining the established one. Network effects enable new technology to exist in niche markets as well as different competitive outcomes to occur, i.e. competitive isolation, competitive convergence and competitive disruption. With weak network effects, when mainstream and niche markets are served by different companies and depend on a preference structure, the potential for technology disruption exists. Strong network effects, however, prevent niche creation and disruption regardless of the preference structure of consumers.

The manner in which consumer network structures influence such technological disruption also forms the subject of this investigation. The model and simulated influence of network effects assumes the inter-connectedness of all consumers within the population and the existence of a complete network. This assumption is tempered by consideration of the different ways in which consumers connect to each other within social networks, i.e. regular, lattice, small-world, and random networks characterized by clustering and path length properties. Even within the case of strong network effects, a consumer network characterized by high clustering and long path length provides favorable conditions for new potentially disruptive technology to survive in niche groups. Regular and small-world networks with few shortcuts fall within this category. Random networks that exhibit low clustering and short path-length properties favor established technology, enabling it to remain dominant in the market. Even under the favorable conditions of consumer network structures, a Firm introduces a new, potentially disruptive technology requiring the creation of a critical mass if it is to enter the mainstream sector. Drawing on Witt's concept (1997), diffusion actors are required to coordinate adoption within mainstream sectors and to create critical mass.

The empirical section of this doctoral thesis identifies determinants of technology acceptance characterized by disruptiveness and network effects. The theory of planned behavior and the technology acceptance model provide a basis for the proposed model. An online survey was administered, while crowdsourcing together with social media were utilized to collect primary data on German and Indonesian users' acceptance of technologies or applications in long-distance calls. The expected current and future number of users, representative of the technology's installed base, were found to be positively and significantly (albeit indirectly) related to their intention to use the technology. Perceptions of affordability and ease of use were also positively and significantly related to the attitude toward using which subsequently had an important relationship with an individual's intention to employ the technology. We observe a connection between the proposed conjecture from second paper (Chapter 3) and empirical finding of the third paper (Chapter 4). In the second paper, the discussion conclude that consumer networks characterized by high clustering and long path length are recognized to be favorable for a new technology to survive. The third paper provides empirical evidence through the finding of users' actual use of long-distance calls devices in Germany and Indonesia. Germany, as an individualistic society characterized by low clustering and short path length, allows the established technology, i.e., fixed-line telephone, to still dominates. Indonesia, on the contrary, as a collectivistic society and characterized by high clustering provides a more favorable condition for new technology in messaging-service apps to survive and to eventually get adopted by mainstream consumers.

1.6 Structure of the doctoral thesis

The present thesis, consisting of three papers, seeks to shed light on how network effects influence the potential for technology disruption by scrutinizing the mechanism of disruptive technology in social networks. The first paper, by means of agent-based modeling and simulation, analyzes the dynamics of technology competition as the interplay between companies and customers in a market featuring heterogeneous consumers. Depending on the strength of the network effects, consumer preference heterogeneity plays an important role in determining competitive outcomes. The second paper, intended to be an extension of the first, by abandoning the firm assumption of a complete network implied there, proposes a theoretical concept of how different consumer network structures affect the competitive outcomes, including competitive disruption. Consumer networks are characterized by high clustering and long path length, such as regular network topology, and small-world with a limited shortcut topology. These constitute more favorable conditions in which new, potentially disruptive technology can survive. The third paper, departing from the theoretical domain to engage in an empirical exercise, investigates the determinants of acceptance of disruptive technologies as characterized by network effects in Germany and Indonesia. This bi-lateral comparison not only explores differing developed and developing country contexts, but also highlights the contrasts in individualistic and collectivistic societies (from a sociological perspective) or those with both high and low degrees of connectivity (from a social network perspective).

A connection between the proposed conjecture contained in the second paper (Chapter 3) and the empirical findings of the third (Chapter 4) can be observed. In the second paper, the discussion concludes that consumer networks characterized by a high level of clustering and long path length are favorable to a new technology's survival. The third paper provides empirical evidence in the form of respondents' actual use of long-distance call devices in Germany and Indonesia. The former, as an individualistic society characterized by low clustering and short path length, facilitates the continuing dominance of established technology, namely; the fixed-line telephone. In contrast, Indonesia, as a collectivistic society characterized by high clustering, provides more favorable conditions for novel technology in messaging-service apps to survive and to achieve eventual adoption by mainstream consumers.

The frame of thought and connection between the three papers contained in this thesis are illustrated in Figure 1.2 below.

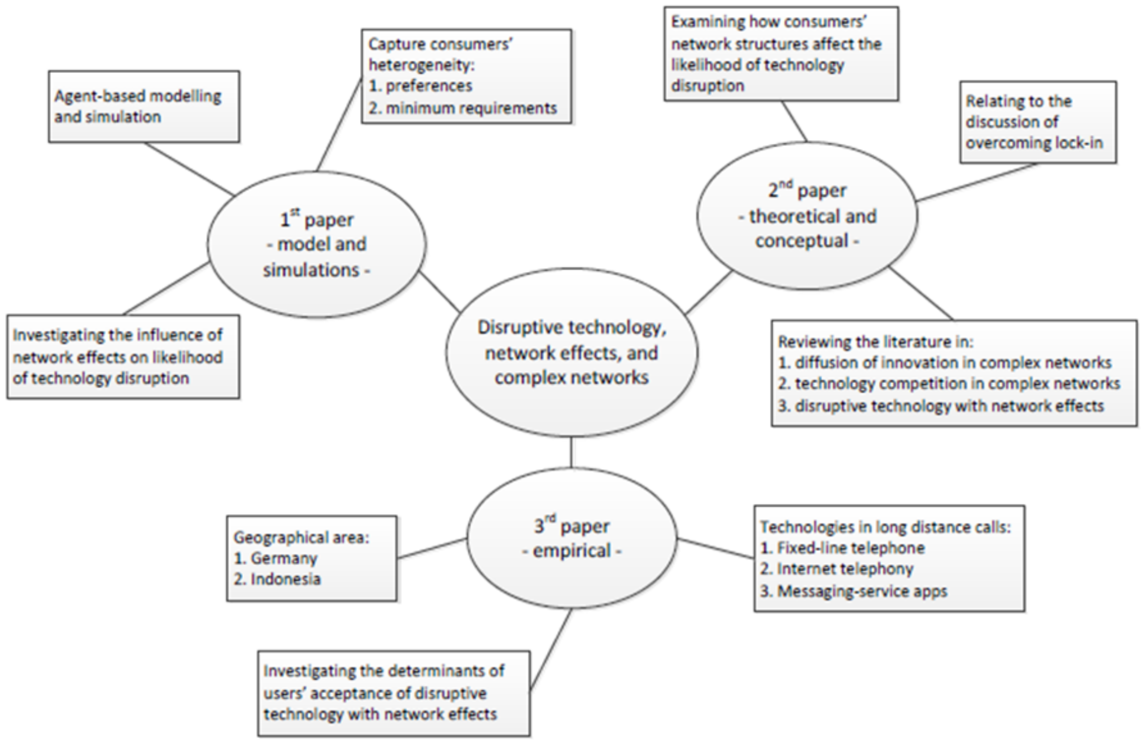

Figure 1.2 Frame of thought and connections among three papers

Chapter 2: Investigating the Influence of Network Effects on the Mechanism of Technology Disruption

This chapter investigates the influence of network effects on the mechanisms and probability of technology disruption. It begins with a brief survey of disruptive technology theory and network effects. Previous studies on formal models and simulations of disruptive technology are also reviewed.

The first paper utilizes agent-based modeling and computer simulation to capture the range of consumer preferences and minimum requirements, as well as provider / customer interplay. Companies introduce product and process-related innovations to improve product performance and reduce costs. Consumers consistently evaluate products and make adoption decisions by maximizing their utility based on product performance and network effects or the number of adopters. The market consists of both mainstream and niche segments. Weak and strong network effects, in addition to the homogeneous and heterogeneous preferences of consumers, are tested.

The results indicated that in contexts where network effects prove to be weak, different competitive regimes become possible. Homogeneous preferences in mainstream and niche segments allow for competitive isolation, while heterogeneous preferences result in competitive convergence and disruption. Strong network effects, however, lead to winner-takes-all and lock-in outcomes regardless of the heterogeneity of consumer preferences.

Chapter 3: Competition and Disruptive Technology in Social Networks

As part of a theoretical paper investigating the influence of consumer network structures on the probability of technology disruption, an extensive literature review encompassing several domains of research was conducted. This comprised literature on disruptive technology, network effects, social networks, diffusion of innovation and technology competition in social networks.

Drawing on the literature regarding the diffusion of innovation, technology competition and social networks, it is understood that the influence of consumer network structures on market dynamics and competitive outcomes cannot be ignored. Omitting consumer network structures from the technology competition model is potentially misleading, especially when network effects are present, in terms of overemphasizing an installed base.

The chapter provides a ‘map’ of different network structures and their relevance to both technology competition and the probability of technology disruption. A conjecture is proposed in this study of how a new and potentially disruptive technology might survive in a niche, form a critical mass and subsequently 'attack' the mainstream market.

Chapter 4: Acceptance of Disruptive Technology with Network Effect: An Empirical Study of Long Distance Calls in Germany and Indonesia

Chapter 4 investigates the determinants of user acceptance of disruptive technologies in long-distance calls in Germany and Indonesia, commencing with a brief review of disruptive technology theory and network effects.

The empirical study contained in the third paper employed an online survey distributed to German and Indonesian respondents via a crowdsourcing and social media platform as a means of eliciting primary data. The resulting information was analyzed using a series of multiple regressions with Stata. The model is based on a Theory of Planned Behavior and Technology Acceptance combined with several variables related to network effects. The paper investigates three long distance call technologies, i.e. fixed-line telephone, internet telephony such as Skype, and messaging-service apps, for example, WhatsApp. From the data collected about the three different product technologies, comparisons between two were made by taking the difference in the mean value of each variable. Three cases of regression, each consisting of twelve variables, based on the comparisons were developed; (1) internet telephony vs. fixed line (2) messaging service apps vs. fixed line and (3) messaging service apps vs. internet telephony.

In all cases, the results confirmed that the difference in intention to use has a positive relationship with the difference in actual use. Moreover, the difference in attitude toward use has a positive relationship with difference in intention to use. However, the relationship between the difference in perceived behavioral control and the difference in intention to use was found to be insignificant across the board. Mixed results concerning the relationship in difference of subjective norm and the difference in intention to use emerged, complete details of which are presented in Chapter 4.

2 Investigating the influence of network effects on the mechanism of disruptive technology

2.1 Introduction and Motivation

Since its introduction by Christensen in his seminal book, “The Innovator’s Dilemma”, published in 1997, disruptive technology theory has exerted a significant influence on scholars and managers in their attitude to technology competition. While the previous literature on this subject highlighted the displacement of established companies and technologies driven by the superior performance of entrants to the market and new technology (Dosi, 1982; Foster, 1986), the notion of disruptive technology raised the possibility that technology providing inferior performance could, nevertheless, undermine or displace the incumbent.

Modern technologies, such as those in the fields of information and communication technologies (ICT), deliver increasing returns on their adoption (Keller and Hüsig, 2009; Vaishnav, 2008). When two or more technologies compete, such returns on adoption will result in positive feedback. In other words, the greater the adoption of the technologies, the more familiar they become to users and the greater the extent to which they are improved (Arthur, 1989). This, in turn, promotes more extensive user adoption of the technologies in question and creates lock-in. Within the context of Arthur’s rival technologies, two or more compete for adopters in the mainstream market. Disruptive technology is inferior compared to established technology but offers other attributes, such as enhanced convenience, reduced costs and greater simplicity, that were initially only attractive to a niche market (Christensen, 1997). In this paper, the competition dynamics between an established technology and a novel, potentially disruptive variety isinvestigated. The model adopted here will be different to that employed by Arthur (1989) since potentially disruptive technology will initially enter from a niche, low-end market segment, rather than directly competing head-to-head with established technology in the mainstream market segment. Drawing on the work of Adner and Zemsky, 2005; Vaishnav, 2008; and Mount, 2012, the lack of an explicit formulation of network effects’ influence on the formal model of disruptive technology will be identified.

Greater attention will be specifically paid to how increasing returns on its adoption influences the ability of a potentially disruptive technology to undermine established ones. Previous studies have highlighted many examples of disruptive technologies within the field of ICT (Yu and Hang, 2009; Hüsig et al. 2009) producing network effects. However, the manner in which these influence the mechanism of technology disruption has received only limited attention. Therefore, these two research streams have been combined by taking into account the network effects on the mechanism of technology disruption (Figure 2.1). This will be achieved by developing a formal disruptive technology model that explicitly includes the increasing returns on the adoption of network effects. After a careful review of several studies investigating the formal model of technology disruptive mechanism (Adner, 2002; Buchta et al, 2004; Adner and Zemsky, 2005; Vaishnav, 2008; Mount, 2012), the lack of an explicit formulation of network effects' influence on the formal model of disruptive technology will be identified.

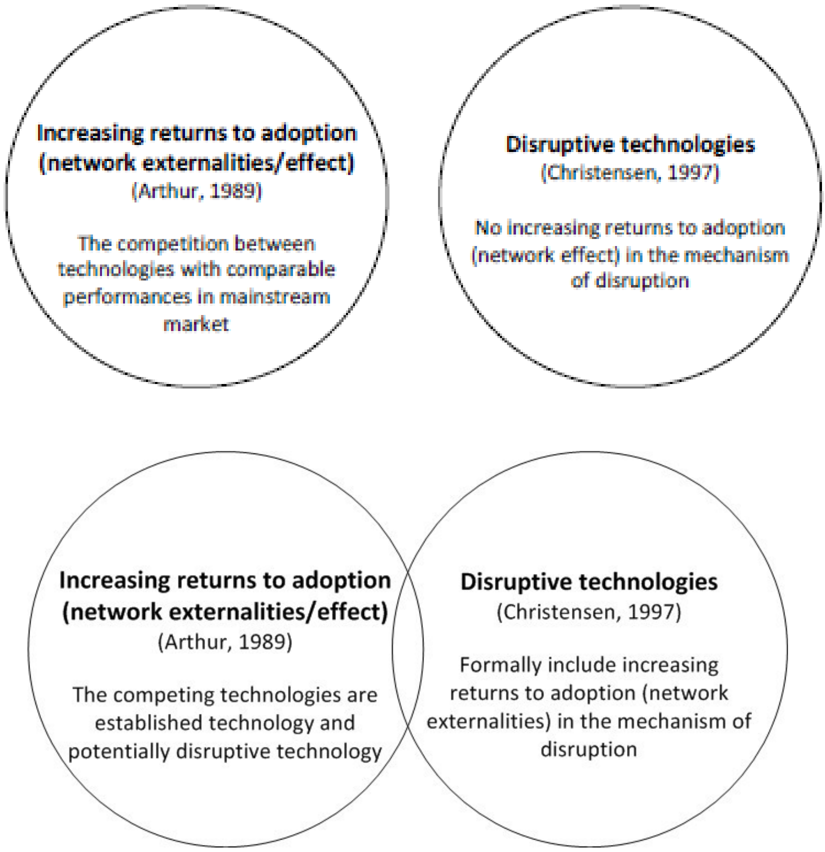

Figure 2.1 Research motivation in combining the network effects and disruptive technology

While it is understood that disruption is enabled by performance oversupply of established technology and enacted by the lower price of potentially disruptive technology (Adner, 2002; Govindarajan and Kopalle, 2006), strong network effects might prevent disruption occurring. This result would be expected from the model. Furthermore, since network effects are not dichotomous, i.e. present or absent (Srinivasan, et al., 2004), but exist in varying degrees, the influence of different degrees of network effects on the probability of disruption will be investigated.

To investigate how network effects influence the probability of disruption as well as determining competitive outcomes, agent-based modeling and simulation (ABMS) is employed. Besides all other advantages and reasons, its extension possibilities are of particular interest. For example, in this study, consumer preferences and network effects were set up as determining parameters among all other parameters. In accordance with the requirements and purpose of the research, certain exogenously and arbitrarily determined parameters can be turned into variables and endogenously generated. Another extension possibility could be to relax some strong assumptions, such as that of the perfect knowledge of consumers in evaluating product characteristics Adner and Zemsky, 2005; Vaishnav, 2008; Mount, 2012). Against this background, the lack of an explicit formulation of network effects' influence on the formal model of disruptive technology will be identified.

While it is understood that disruption is enabled by established technology performance oversupply and by the lower price of potentially disruptive technology (Adner, 2002; Govindarajan and Kopalle, 2006), strong network effects might prevent disruption from occurring. This result is to be expected from the model. Furthermore, since network effects are not dichotomous, i.e., either fully present or completely absent (Srinivasan, et al., 2004), but present in degrees, an investigation of the relationship between this range of network effects and the lprobability of disruption is desirable.

In order to investigate how network effects influence the probability of disruption as well as determining competitive outcomes, agent-based modeling and simulation (ABMS) was employed. In addition to all other advantages and reasons, its extension possibilities were of particular interest. For example, in our study consumer preferences and network effects were set up as determining parameters among all other parameters. Depending on the purpose and requirements of the research, certain exogenously and arbitrarily determined parameters could be turned into variables and endogenously generated. Another extension possibility could be to relax a number of strong assumptions, such as that of perfect knowledge on the part of consumers in evaluating product characteristics.

2.2 Disruptive technology

According to Christensen, disruptive technologies are those providing different values from mainstream technologies which are initially inferior to the latter along the dimensions of performance that are most important to mainstream customers. Christensen introduces the aspects of changing performance over time, plots the trajectories of product performance provided by companies and demanded by customers for different technologies and market segments and shows that technology disruption occurs when these trajectories intersect (Figure 2.2).

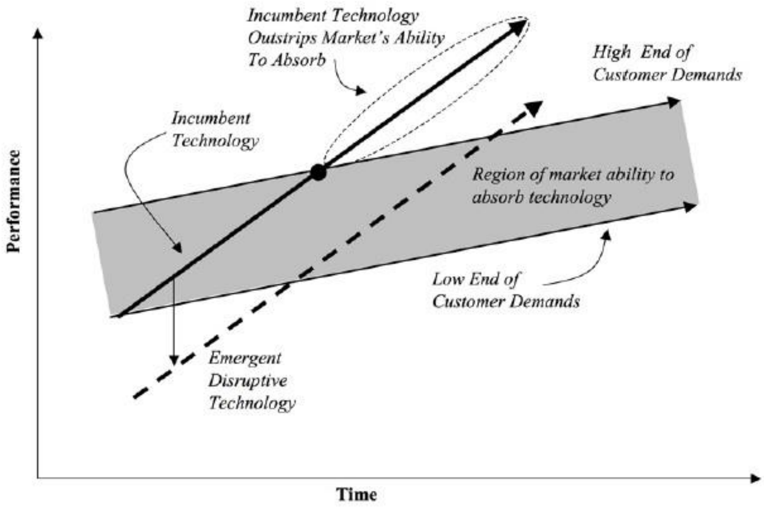

Figure 2.2 Disruptive technology model (Krikos, 2011)

Any product based on disruptive technology can only serve a niche segment in its early stages. However, further development could raise its performance to a level sufficient to satisfy mainstream customers. Although improved, such enhanced performance remains inferior to that of established mainstream technology, which is also improving. Over time, the performance of mainstream technology would exceed the demand of mainstream customers, resulting in performance overshoot. Market disruption occurs when the new product, based on disruptive technology, displaces the mainstream product in the mainstream market (Yu and Hang, 2009).

As mentioned in the last-mentioned authors' work, a heated debate has been engendered over the definition and scope of disruptive innovation. A number of researchers supported Christensen's position, while others proposed their own slightly different view. Others criticized the vagueness of the concept. For instance, Govindarajan and Kopalle (2006) contributed a series of analyses to establish the reliability and validity of the disruptiveness scale. According to their measurements, disruptive innovation should (1) be inferior in those attributes valued by mainstream customers, (2) offer innovative value propositions to attract a new customer segment or the more price-sensitive mainstream market; (3) be sold at a lower price and (4) penetrate the market from niche to mainstream.

2.3 Network effects and lock-in

When two or more technologies compete, increasing returns on adoption create positive feedback, i.e., wider adoption renders the technologies more familiar to users, with the result that they are further improved (Arthur, 1989). This, in turn, promotes wider user adoption of the technologies and, eventually, creates customer lock-in. When two or more technologies compete within a market of potential adopters an 'insignificant event' might favor one technology, enabling it to achieve sufficient adoption and eventually dominate, resulting in a winner-takes-all outcome. Arthur (1989) provided a dynamic model that demonstrates how insignificant or random historical events influence the selection of the market outcome of multiple equilibria. Lock-in might result in inefficiency problems, i.e. the dominance of inefficient technology that prevents superior technology entering the market.

Arthur (1989) suggested that consumers value a product or technology for two reasons; their intrinsic preference for it but also because of the number of users who have already adopted the technology. In other words, intrinsic preference and the number of users determine the utility of a particular form of technology for adopters. Arthur is specifically interested in the increasing returns on adoption where the utility of a specific technology for a new user increases with the number of others who have already adopted it (network effect).

Srinivasan, et al. (2004) posit an important notion of the nature of network effects. They asserted that network effects are not a matter of being present or absent, but one of degree. In their empirical study investigating the effect of network externalities on pioneer survival, they employed different groups of raters, academic experts and managers, to measure (direct and indirect) network effects of more than 40 product technologies. They investigated those with low network effects, such as electric toothbrush and pocket calculators, in addition to product technologies with very high network effects, for example, fax machines and operating systems for personal computers. They related the different degree of network effects of those technologies with the survival of a "pioneer", defined as the Firm which first introduced the corresponding technology. In this study, it is the different degree of network effects' implications for rival technologies and their competitive outcomes that becomes the central focus.

2.4 Review on some disruptive technology models and simulations

Some scholars worked to formalize disruptive technology theory and offered some theoretical insights into the mechanism and determinants of disruption (Adner, 2002; Adner and Zemsky, 2005; Buchta et al., 2006; Mount, 2012; Vaishnav, 2008). Other scholars formalized the technology competition dynamics similar to disruptive technology theory without mentioning the terminology (Malerba et al., 2007).

Adner (2002) emphasized the demand structure that determines the dynamics of disruptive technology and its impact on a competitive regime. He proposed preference overlap and asymmetry as novel constructs which characterize different market segments and an explanation as to how these constructs lead to disruption as one of the competitive regimes. Based on field research, Vaishnav (2008) offered an analysis of why a potentially disruptive technology fails to challenge the incumbent dominant technology by looking at technical, commercial and organizational uncertainties. Building on existing models of innovation diffusion, Mount (2012) suggested that development dynamics, preference structure and demand structure all have an effect on market disruption. Buchta et al. (2004), while investigating the effect of a firm's inertia and technology efficiency on the potential for disruption, developed a model that includes technology, market and Firm decisions.

The work of Adner (2002) and Malerba et al. (2007) is central to the present study since they similarly pay particular attention to the demand dynamics of competing technologies for adoption. Adner (2002) demonstrated how his proposed new constructs of preference asymmetry and overlap determined disruption in the hard-disk drive market. Malerba et al. (2007) investigated the role of consumers with different preferences and experimental users in innovation and industry dynamics. They argued that the existence of fringe markets with contrasting preferences and experimental users are crucial for new entrants to eventually become competitive in the main market. Although the model developed here has some similarities, it is argued that certain significant differences exist. Adner (2002) developed a model for disruptive innovation and argued that demand structure in terms of consumer preference overlap and asymmetry determines the competitive outcome, including competitive disruption. However, Adner's model did not take into account the network effect on consumer adoption decisions. Malerba et al. (2007) investigated how consumers with different preferences created space enabling a new technology to compete within the mainstream market segment. This model distinguishes itself from that of Malerba et al. (2007) by incorporating core and secondary functional characteristics as well as the affordability characteristic of technological products. Hence, companies are allowed to develop their products along various trajectories in the product space, in addition to committing themselves to product and process innovation.

2.5 Research objective and hypotheses

A model was formulated that incorporates technology development, consumer decisions and firm allocations as well as the structure of demand in order to achieve the first objective, namely; the simulation of interaction or interplay between those factors. The second objective was to identify the influence of network effects on the probability of disruption as one of the competitive outcomes.

Based on previous studies in the area of disruptive technologies outlined in Section 1.3 above, the following hypothesis was put forward:

> *Hypothesis 1:* The dynamics and outcome of disruption are affected by the interplay between technological development, consumer choice, Firm

decisions and demand structure.

Keller and Hüsig (2009) in their work on the development of an identification framework of disruptive innovation argued that, even if a potentially disruptive technology such as web application has the potential to satisfy the performance requirement of consumers in the mainstream segment, it is unlikely to pose a disruptive threat to established technology in the software industry due to network effects. On the other hand, Vaishnav (2008) suggested that, while a strong network effect can create a winner-takes-all market, a weak network effect might favor entrants. In other words, he argued that the strength of network effects might determine the outcome of the competition. Consequently, the second following hypothesis is proposed:

> *Hypothesis 2:* The strength of network effects influences the probability of disruptive innovation as a competitive outcome.

2.6 Model setup

2.6.1 Supply dynamics

Companies develop their products in a two-dimensional product space consisting of Characteristic 1 in the abscissa and Characteristic 2 in the ordinate. Characteristic 1 might represent the core characteristic of the product, such as quality, while Characteristic 2 might include secondary characteristics, for example, convenience, ease of use and portability.

One group of companies was allowed to focus on developing its products with regard to Characteristic 1 (blue-shaded area), whereas the other focused on Characteristic 2 (orange-shaded area), as illustrated in Figure 2.3 below. At the outset, all commercial enterprises were allocated initial financing, with each committed to investing this endowment fund in product and process innovation. The share of endowment fund allocation varied between companies. During each time period, those turning a profit were allocated further capital for product and process innovation.

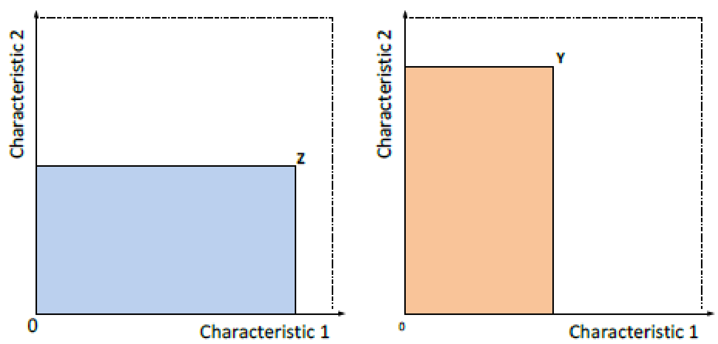

Figure 2.3 Product development areas in the product space

Product innovation

Companies strive to reach the technological frontier, the most advanced technology achieved by others operating within a particular sector of the industry. When one particular Firm is at the frontier, it will develop its own product development path. Nevertheless, it may decide to focus on one characteristic over another (for instance, one Firm develops a product at some point along the product trajectory between 0 and Z, while another develops along a different trajectory from 0 to Y). A product's characteristics are defined as v_i where, i = 1, 2. Hence, v_1 denotes the functional Characteristic 1 or core characteristic, whereas v_2 represents functional Characteristic 2 or the secondary characteristic.

Companies initially invest in conducting R&D to develop along each dimension

$$v_{it} = v_{i(t-1)} + \Delta v_i \tag{1}$$

$$\Delta v_i = \begin{cases} 0, if product\ innovation\ unsuccessful \\ \max\{\alpha_i\ ;\ \beta_i(L_{i(t-1)} - v_{i(t-1)})\}\ if\ product\ \ innovation\ successful \end{cases} \tag{2}$$

where

v_{it} = characteristic i at time t
Δv_i = change in characteristic i
$\alpha_i \in [0,1]$; improvement increment in characteristic i due to product innovation when the Firm is at the frontier;
$\beta_i \in [0,1]$; improvement increment in characteristic i due to product innovation when the Firm is pursuing the technological frontier;
$L_{i(t-1)}$ = technological frontier of characteristic i at $(t - 1)$

The probability P of product innovation success is determined by the allocation of profit π for R&D expenditure, $R_{product}$

$$P \text{ (product innovation is successful)} = 1 - e^{-\gamma(R_{product})} \tag{3}$$

where

$R_{product}$ = R&D expenditure as a share of profit at $t = \theta * \pi_t$ (4)
γ = coefficient of probability function
θ = constant fraction of profit for R&D expenditure

Profit π is calculated in each period t as:

$$\pi_t = M * p - M * k \tag{5}$$

where M = the number of products sold
p = product price
k = production costs

Price p is obtained by adding a mark-up μ to cost :

$$p = k * (1 + \mu) \tag{6}$$

Affordability is the inverse of price and defined as the third characteristic of the product, v_3,

$$v_{3t} = {}^{1}/_{p_t} \tag{7}$$

Process innovation

Companies allocate their initial endowment, and subsequently their profit, to process innovation as a means of reducing the cost k to the negative value of Δk if process innovation proves successful.

$$k_t = k_{t-1} + \Delta k \tag{8}$$

$$\Delta k = \begin{cases} 0, if\ process\ innovation\ unsuccessful \\ -e^{-\sigma t}, if\ process\ innovation\ successful \end{cases} \tag{9}$$

The probability *(P)* of success of process innovation is expressed in the equation below:

$$P \text{ (process innovation is successful)} = 1 - e^{-\emptyset(R_{process})} \tag{10}$$

, where $R_{process}$ = R&D expenditure as a share of profit at (11)

$t = (1 - \theta) * \pi_t$

$\emptyset$ = coefficient of probability function

2.6.2 Demand dynamics

Minimum requirement and functional benefit

Consumers are endowed with a set of minimum requirements. An individual j is associated with a vector $\overrightarrow{m_j} = \{m_{j,1},\ m_{j,2},\ m_{j,3}\}$, which means $m_{j,1}$ is the minimum requirement of consumer j for Functional Characteristic 1, $m_{j,2}$ is the minimum requirement of consumer j for Functional Characteristic 2, and $m_{j,3}$ is the minimum requirement for affordability. The potential set for a consumer of all products X is $v_{i,X} > m_{i,j}$ for all characteristics i.

Therefore, the functional benefit (B) that consumer j derives from product X is defined as:

$$B_{jX} = \left(v_{1,X} - m_{1,j}\right)^a . \left(v_{2,X} - m_{2,j}\right)^b . \left(v_{3,X} - m_{3,j}\right)^c \tag{12}$$

where coefficients *a, b* and *c* represent the weight that a consumer attaches to the first and second functional characteristics, as well as affordability.

Consumer utility and adoption decision

Consumers assess commercially available products based on product benefit, B_j which comprises their functional characteristics and affordability as the inverse of price, and the proportion of consumers who adopt the product or network effect, $D_{j(t-1)}$.

In the utility function, a variable of adoption during the previous time period, $C_{X(t-1)}$ is assigned to prevent a shift in adoption simply because of identical utility value which is defined as follows:

$$C_{X(t-1)} = \begin{cases} 0, if\ X\ is\ not\ adopted\ at\ t-1 \\ 1, if\ X\ adopted\ at\ t-1 \end{cases} \tag{13}$$

Consumer j will adopt product X at time *t* which gives the highest utility U defined as:

$$U^j_{Xt} = qB_{jX} + nD^j_{X(t-1)} + sC_{X(t-1)} \tag{14}$$

where q represents the strength of functional benefit, n represents the strength of network effect, and s is a small constant. $D^{j}_{X(t-1)}$ signifying the network effect or number of adopters of product X at $(t-1)$

2.6.3 Simulation setup

The simulation was developed in collaboration with the Laboratory for Simulation Development (Lsd), an agent-based simulation programming platform built on C++. Lsd written by Marco Valente and developed to facilitate the use of computer simulations in economic research (Valente, 2008).

Using Lsd, a market consisting of companies and consumers was set up. As with Adner's approach (2002), the supply side was represented by two companies competing in the market. This, of course, constitutes something of a simplification, Nevertheless, a Firm featured in our simulation can be considered as representing a group of such commercial enterprises whose product characteristics are similar. Companies 1 can be regarded as a group focusing more on functional Characteristic 1 and vice versa. Firm 1 and Firm 2 start from contrasting initial conditions of their respective Functional Characteristics 1 and 2, as well as the magnitude of development or improvement step of Functional Characteristics 1 and 2 as the result of product innovation, $\alpha 1$ and $\alpha 2$. Companies 1 and 2 conduct product innovation whose success will determine the value of Functional Characteristics 1 and 2 over the ensuing time period. Companies 1 and 2 also implement process innovation, the successful outcome of which will establish cost reduction and price accordingly during the subsequent period. Companies allocate the proportion of profit necessary to influence the probability of successful product and process innovation. The values of the parameters of Companies 1 and 2 are provided in Table I of the Appendices.

The market consists of two segments, mainstream and niche, with consumers falling within either segment. 250 individual consumers were assigned to the mainstream with a further 75 being allocated to the niche segment. Consumers were characterized by their heterogeneity with regard to the minimum requirements of Functional Characteristic 1, Functional Characteristic 2 and affordability. The minimum requirements of Functional Characteristic 1 of consumers consist of being normally distributed with a mean of 75 and a standard deviation of 25. A similar set-up exists for the minimum requirement of Functional Characteristic 2 for consumers. With regard to affordability, the minimum requirements are uniformly distributed between 0 and 2. Every consumer evaluates the Functional Characteristics 1 and 2 as well as the affordability of product technology provided by Companies 1 and 2 during each time period. Consumers will only consider buying a product if it offers functional characteristics that exceed their minimum requirements and offers functional benefit.

Every consumer puts weight either on Characteristic 1 or 2 and affordability as a notion within consumer preference. This weight was set up as a power in consumer's benefit function. In this manner, the heterogeneity of consumer preferences in each segment can be established. In the simulation, homogenous consumer preferences were initially set up followed by heterogeneous ones in the mainstream and niche segments.

This functional benefit, together with network effects, will determine the product utility that can be derived by a consumer. If both products have a positive utility value, a consumer will choose that which offers the higher value. In every time period, consumers make a purchasing decision. Consequently, Companies 1 and 2 will recapitulate products sold, i.e. the number of adopters, at every time period. Total products sold will subsequently, produce Firm profits which, in turn, determine the sustainability of product and process innovation in the short to medium term.

Parameters indicating the strength of the functional benefit and network effects are a feature of the object market. Their values are adjusted to facilitate investigation of the influence of weak and strong network effects on the respective performance of companies in the mainstream and niche segments. The parameter value for functional benefit q was set at 2.0, while the parameter value of network effects n was 0.75 for weak network effects and 4.0 for strong network effects. This extreme set up in the parameter values of network effects was decided upon in order to obtain the differences in weak and strong network effects, since fine and step-by-step adjustments in the parameter values of such effects result in almost identical results.

2.7 Results

2.7.1 Homogenous consumer preferences

Homogeneous preferences can be said to exist when all consumers in a given market segment demonstrate the same preferences, e.g. all consumers in a mainstream segment attach more weight to Functional Characteristic 1, whereas all consumers in a niche segment do so with regard to Functional Characteristic 2. From an aggregate market perspective, however, it can be said that consumer preferences are heterogeneous. The set-up of the simulation was designed to explore the validity of Christensen's 1997 concept by addressing a niche segment whose preferences differed from those of the mainstream segment. This approach was similarly adopted by Malerba, et al. (2007) when investigating the role of experimental users and consumers with contrasting preferences toward innovation.

In this case, consumers in the mainstream segment valued Characteristic 1 higher than Characteristic 2 (a = 2.0, b = 1.0), while the opposite was true for those in niche segments (a = 1.0, b = 2.0).

Weak network effect

In a weak network effect situation (n = 0.75), the result was as expected as shown in the Figure 2.4 below. The parameter of benefits from product characteristics (q) at a value of 2.0 was maintained across all simulations.

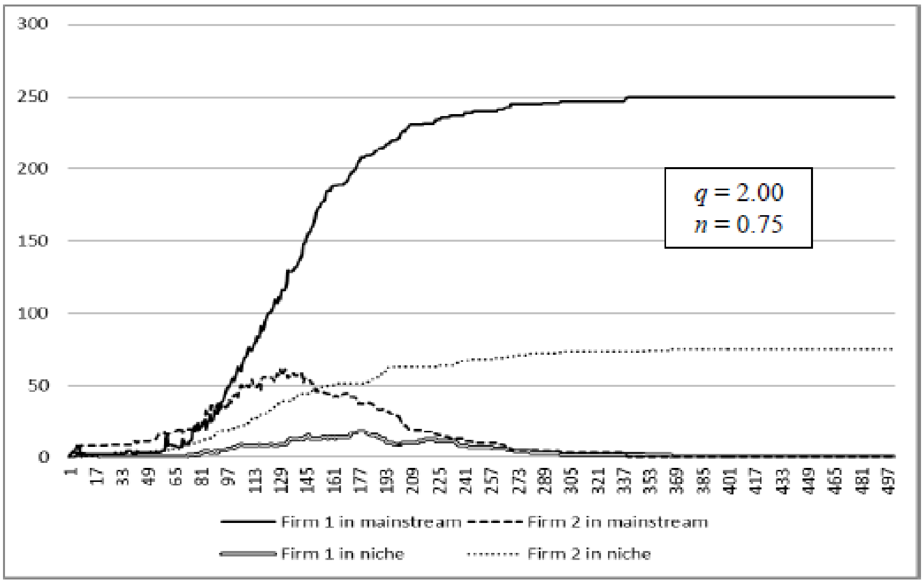

Figure 2.4 Competitive isolation, Firm 1 operates in the mainstream and Firm 2 operates in a niche

Firm 1 operated in and dominated the mainstream segment and Firm 2 a niche segment. In this weak network effect context, consumer preferences in each segment are significant and, therefore, determine the competitive outcome, i.e. competitive isolation. Consumers' minimum requirement of Functional Characteristics 1 and 2 which are normally distributed determine the shape of the S-adoption curve both in the mainstream and niche segments.

Strong network effect

Firm 1 dominates the mainstream as well as the niche segment in a situation where network effects are strong (n = 4.0). Even if all consumers in a niche segment attach more weight to Functional Characteristic 2 than Functional Characteristic 1, whereas consumers in the mainstream segment do the opposite, eventually all consumers in both segments adopt the product technology of Firm 1 due to strong network effects, as shown in Figure 2.5 below.

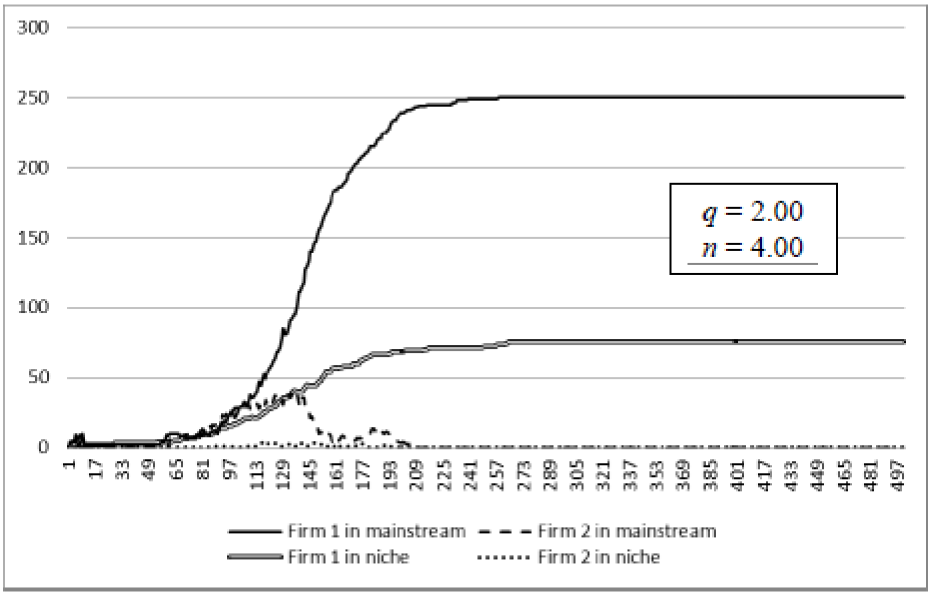

Figure 2.5 Firm 1 dominates the mainstream and niche segments

2.7.2 Heterogeneous consumer preferences

Weak network effect

In the previous scenario of homogenous preferences, all consumers within the mainstream segment placed more weight on Functional Characteristic 1 than Functional Characteristic 2, a scenario reversed for all those in the niche segment.

The heterogeneity of preferences in the mainstream segment was introduced by modifying the proportion of consumers with different preferences. Initially, all consumers within the mainstream segment put more weight on Functional Characteristic 1 than Functional Characteristic 2. It was subsequently established that 50 out of 250 consumers attached more weight to Functional Characteristic 2 than 1 by applying a weighting of a = 1.0 and b = 2.0. The focus here is the adoption of product technology by Firm 2 in the mainstream segment. In the niche segment, the homogeneity of consumer preference toward Functional Characteristic 2 was maintained, with the parameter of functional benefits q at 2.0 and the parameter of network effects n at 0.75. The results were as follows:

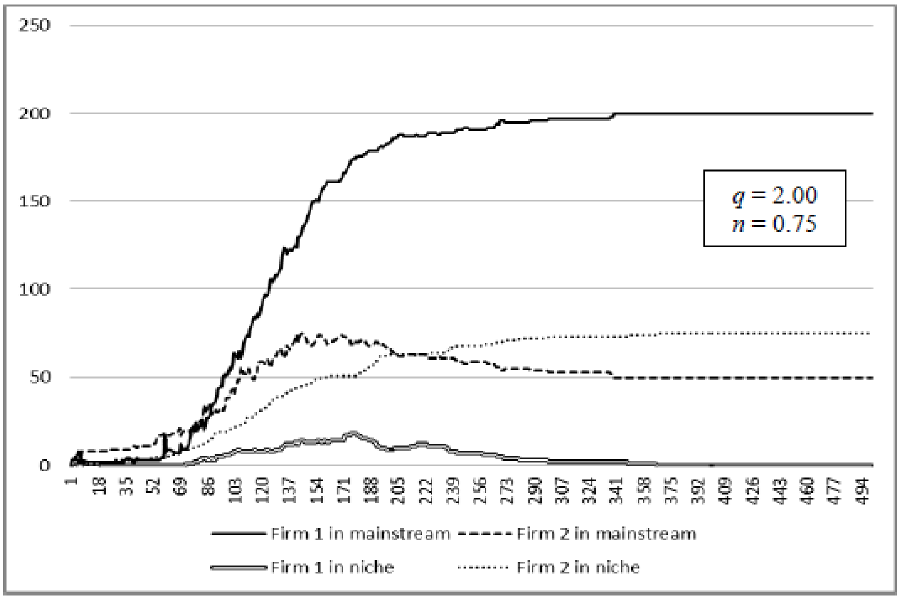

Figure 2.6 Competitive convergence: both Firm 1 and Firm 2 operating in the mainstream

The result in Figure 2.6 shows that some consumers in the mainstream segment adopt product technology from Firm 2. Companies 1 and 2 co-exist in the mainstream segment, in other words, there is competitive convergence, while Firm 2 continues operating in a niche segment.

The proportion of consumers in the mainstream segment whose different preferences were greater was adjusted, we now set 140 consumers put more weight on Functional Characteristic 2 than Functional Characteristic 1 by setting parameter a = 1.0 and b = 2.0, as we did previously. No adjustment was made to either the parameters of functional benefit q or network effects n for consumers in the niche. The results are shown in Figure 2.7 below:

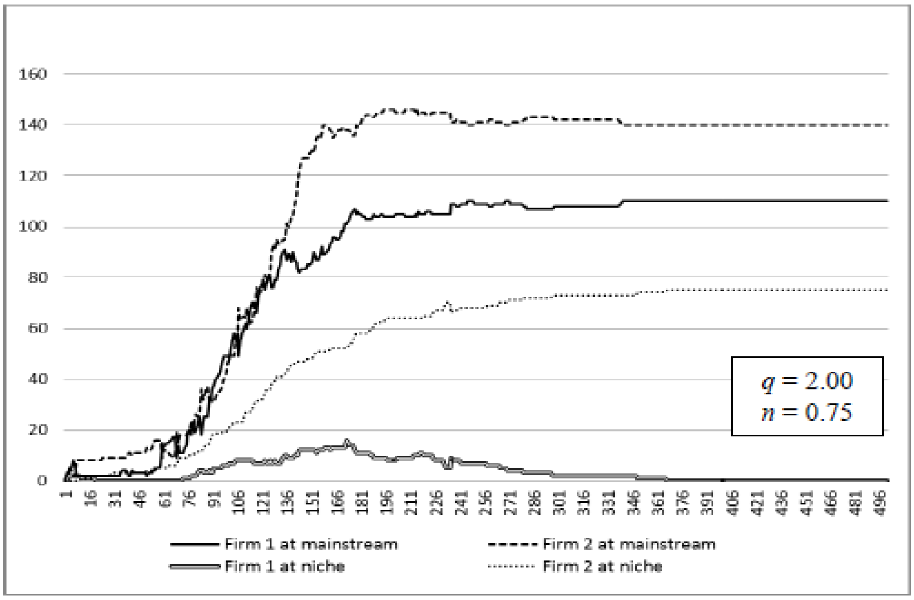

Figure 2.7 Competitive disruption: Firm 2 supercedes Firm 1 in the mainstream segment

In the mainstream segment, more consumers adopt product technology from Firm 2, while that commercial entity maintains its operation in niche. This result suggests the existence of competitive disruption since the product technology of Firm 2 is adopted to a greater extent than that of Firm 1.

Strong network effect

As with the case of homogeneous preferences outlined above, Firm 1 dominates the mainstream as well as the niche segment in a situation where network effects are strong (n = 4.0). Even if all consumers in a niche segment harbor a pronounced preference for Functional Characteristic 2 and consumers in the mainstream segment are characterized by heterogeneous preferences, eventually all consumers in the niche adopt the product of Firm 1 due to strong network effects, as shown in Figure 2.8 below.

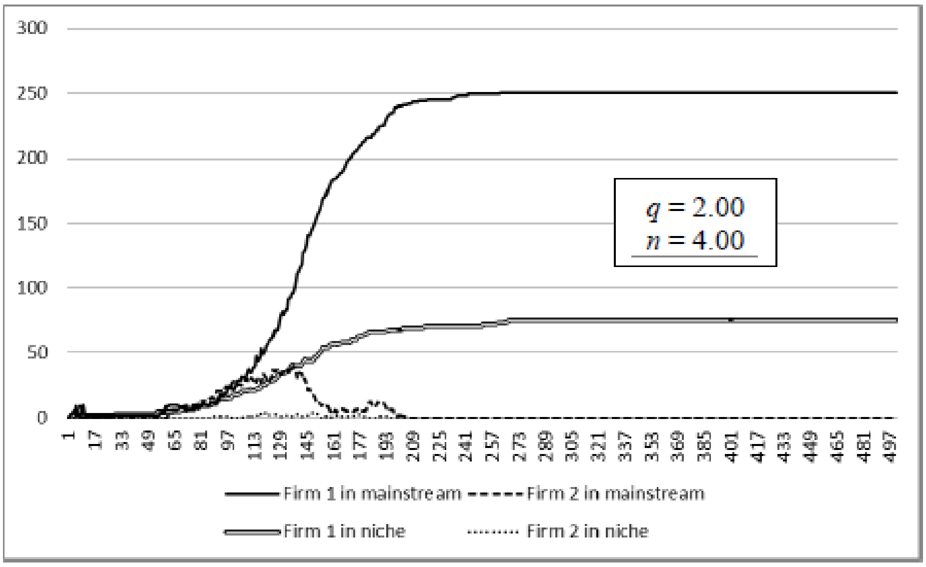

Figure 2.8 Firm 1 dominates in both mainstream and niche segments regardless of the preference heterogeneity of consumers

2.8 Discussion

Multi-segment markets demonstrating homogeneous preferences for weak network effect situations allow competitive isolation outcomes. For the purposes of the study reported here, a multi-segment market is assumed to be one consisting of both mainstream and niche segments. Such markets with homogeneous preferences emerge when consumers in a mainstream segment demonstrate a uniform preference for certain product technology characteristics. In contrast, consumers in niche segments also harbor uniform preferences albeit for different characteristics. Competitive isolation suggests that consumers in mainstream markets adopt product technology with certain characteristics, whereas those in niche markets favour product technology possessing other characteristics. From a supply-side perspective, Firm 1 operates within a mainstream segment, whereas Firm 2 works in isolation within a niche segment. However, in a market where homogeneous preferences and network effects prove to be strong, monopolies emerge. Firm 1 is completely dominant in the mainstream and niche sectors. This scenario represents a winner-takes-all situation similar to that presented in Arthur's model.

Markets characterized by heterogeneous preferences and weak network effects allow for both competitive convergence and competitive disruption to occur. A heterogeneous preference situation refers to one where mainstream segment consumers hold different preferences, i.e. a number of them favour Characteristic 1, while others lean towards Characteristic 2. Competitive convergence occurs when commercial entities co-exist and operate within the mainstream segment. As argued by Malerba, et al. (2007), this result confirms the notion of diverse preferences enabling new companies with innovative technology to survive.

At some point, when the consumers in the mainstream segment whose preference for Functional Characteristic 2 exceeds that for Functional Characteristic 1, competitive disruption might occur in the market resulting in a heterogeneous preference and weak network effects situation. For simulation purposes, the proportion of consumers in the mainstream segment whose preferences differed was exogenously established. The sources and mechanisms of changing consumer preferences were not addressed since they fall outside the scope of this study. In the literature, the changing preferences of consumers can be identified from research in the field of psychology, although economists have recently focused attention on the relevance of preference change to their academic discipline (Bowles, 1998; Janssen and Jager, 2001; Witt, 1991). The presence of strong network effects, however, again leads to monopoly regardless of the heterogeneity of consumer preferences.

Lock-in and heterogeneity of consumers' network effects: a discussion

Previous empirical studies provide actual examples of how strong network effects can prevent disruption. Keller and Hüsig (2009) analyzed how Google's web-based office applications have only limited potential to disrupt the established Microsoft desktop office applications due to strong network effects. Vaishnav (2008) observed that, while some information and communications sector technologies, e.g. P2P service providers, promoted major industry changes and showed a promising prospect of disruption, other technologies, such as open source software and Wi-Fi mesh networks, showed no sign of provoking industry disruption.

In this discussion, the issue of lock-in is addressed since it represents one of the competitive outcomes in the simulation presented here. When strong network effects yield the same result of a winner-takes-all situation and consumers are locked into one technology, the question is one of how to prevent lock-in or what situation can forestall the occurrence of lock-in. Heterogeneity in consumer preferences seems unable to overcome strong network effects. However, real-life examples suggest that, despite the presence of network effects, competing technologies can operate simultaneously or coexist within the same market.

In a typical economic model, Shurmer (1993) pointed out that network effects are assumed to be uniform across all consumers. In his empirical study of software program applications, he further argued that network effects vary among consumers since they are derived from different sources. While popular examples, such as the dominance of the QWERTY keyboard or alternating current in the technology of electric light and power systems in US and Europe (David and Bunn, 1988; Arthur, 1989) exist, Shurmer highlighted competing product technologies with network effects that co-exist within the market, for instance, WordPerfect and WordStar that dominated the word-processing market in the UK in the early 1980s. He showed that the network effects of any software packages are derived from several sources, including add-ons, books, training courses, and so forth. Shurmer also found that the relative importance of each source varies across different types of users. Therefore, he introduced the notion of heterogeneity of network effects across individual consumer.

In the study reported here, strong network effect is represented by parameter n whose value is 4.0 (while the functional benefit parameter q derived from product features has a value of 2.0) across all consumers in the mainstream as well as in the niche segment. As explained above, the variety of network effects among consumers means that each individual has his or her own strength of network effects relative to that of every other network effect component. Applying to this simulation, the network effects of every consumer in the mainstream and niche segments may be set as random values uniformly distributed between 0 and 4. Hence, average network effects for all consumer values will be 2.0, signifying relatively low or weak network effects. The latter allow for competing technologies to co-exist in the market or, in other words, prevent lock-in. Cantner and Vanuccini (2016) addressed the notion of avoiding lock-in through the presence of user heterogeneity. Using results, it might be possible to refine the notion of user heterogeneity to not only include heterogeneity in user preferences, but also that with regard to network effects across users or consumers.

Following up on the line of thought outlined above, heterogeneity in network effects across consumers allows for weak total network effects, subsequently enabling multiple equilibria to occur. Strong network effects could indicate that heterogeneity of network effects across consumers is absent. To investigate how and why this proves to be the case might represent a valid direction for future research.

Limitation

In this study, it is the total number of users within a defined population or global network which influences the utility which an individual derives from a product and which subsequently influences his/her adoption decisions. The underlying assumption is that any individual consumer is connected to every other counterpart within the population. This is, of course, a strong assumption, since it can be observed that, in reality, the decision of any individual might only be influenced by a local network composed of, for example, family, friends or working colleagues. This limitation could pave the way for a future research initiative. In the following stage, it is intended to dilute the assumption and take a step further by including local networks in consumer adoption decisions. In so doing, it is intended to incorporate social network analysis and utilize complex network structures, such as the small-world network. It is believed that observing the manner in which network structure influences competitive outcome and the probability of disruption will be of interest.

Secondly, it is assumed that consumers have perfect knowledge in evaluating product characteristics. Again, this must represent a strong assumption because, more often than not, consumers do not possess such awareness of product characteristics. The reasons for such shortfalls in consumer knowledge could be due to their having limited access to information, a lack of time to undertake meaningful research, or just laziness because they think it not worth the effort (Valente, 2012). Addressing consumers' lack of competence in evaluating product characteristics in the realm of bounded-rationality concept would constitute an exciting future research topic.

Thirdly, empirical validation is lacking in this study. Case studies demonstrating disruptive technologies working in different degrees of network effects situation along with the corresponding competitive outcomes might be preferable to provide empirical supports.

2.9 Conclusion

This study's first hypothesis is addressed by incorporating technology development, Firm allocation and actions, consumer decisions, and demand structure in the model presented here. It is also addressed by running a simulation mirroring the interaction between companies and consumers in the various market segments and the interplay between market segment preferences and different degrees of network effect.

The second hypothesis was tested and the simulation results suggest that weak or limited network effects allow different competitive regimes, i.e. competitive isolation, convergence or disruption, to emerge. Heterogeneity in consumer preferences matters and influences competitive outcomes. Competitive isolation, where two product technologies operate in their own segment, results when consumers in a segment harbour homogeneous preferences for a specific product technology. Competitive convergence, when one product technology operates not only in its own segment but also in another, creating a situation where two product technologies co-exist within a segment, results from consumer preference heterogeneity. Competitive disruption, when product technology from a niche segment succeeds in gaining wider adoption in the mainstream segment, emerges when the proportion of consumer preferences regarding 'new' product technology increases within the mainstream segment. Strong network effects, on the other hand, will always lead to a winner-takes-all and eventual lock-in situation.

2.10 Appendix

Table 2.1 Parameters of object Firm in the simulation

Parameter	Description	Firm 1	Firm 2
γ	coefficient of probability function of product innovation	0.09	0.09
ϕ	coefficient of probability function of process innovation	0.10	0.10
θ	fraction of profit for R&D expenditure	0.60	0.60
μ	coefficient for mark-up (cost to price)	0.20	0.20
σ	coefficient for cost reduction	0.01	0.01
$\alpha 1$	improvement increment of functional characteristic 1 if product innovation is successful, when firm is in frontier	1.00	0.50
$\alpha 2$	improvement increment of Functional Characteristic 2 if product innovation is successful, when Firm is in	0.50	1.00
β	coefficient of improvement increment if product innovation successful, when the Firm is pursuing	0.50	0.50
2	improvement increment of functional characteristic 2 if product innovation is successful, when firm is in frontier	0.50	1.00
β	coefficient of improvement increment if product innovation successful, when firm is pursuing technological frontier	0.50	0.50

Table 2.2 Variables of object Firm in the simulation

Variables	Description	Firm 1	Firm 2
Profit		10	10
Cost		50	50
Characteristic 1	initial value of characteristic 1	15	10
Characteristic 2	initial value of characteristic 2	10	15
Cheapness	initial value of cheapness	0	0
Product R&D		1	1
Process R&D		1	1
Improvement1	improvement increment of characteristic 1	0	0
Improvement2	improvement increment of characteristic 2	0	0
Market share		0	0
Product Sold_main	number of products sold (adopters) in mainstream	0	0
Product Sold_niche	number of products sold (adopters) in niche	0	0
Product Sold_total	total number of product sold (total number of adopters)	0	0

Table 2.3 Parameters of object Consumers (mainstream and niche)

Mainstream segment (250 consumers)

Parameters	Meaning	homogeneous		heterogeneous			
		value	# of consumers	value	# of consumers	value	# of consumers
a	weight on Characteristic 1	2	all	2	variables	1	variables
b	weight on Characteristic 2	1		1		2	
c	weight on affordability	0.5		0.5		0.5	
min_Characteristic 1 min_Characteristic 2 min_Cheapness		normally distributed with mean of 75 and s.d. of 25 normally distributed with mean of 75 and s.d. of 25 normally distributed with mean of 1.5 and s.d. of 0.25					

Niche segment (75 consumers)

Parameters	Meaning	homogeneous		
		value	# of consumers	
a	weight on characteristic 1	1	all	
b	weight on characteristic 2	2		
c	weight on cheapness	0.5		
min_characteristic 1 min_characteristic 2 min_cheapness		normally distributed with mean of 75 and s.d. of 25 normally distributed with mean of 75 and s.d. of 25 normally distributed with mean of 1.5 and s.d. of 0.25		

Note:

- The niche segment has been maintained as homogeneous since the focus of interest in this research is the heterogeneity of consumer preferences within mainstream segments and the probability of consumer adoption of products from Firm 2 in the mainstream segment.
- To ensure early adoption, low minimum requirements for functional characteristic 1 and 2 (normal distribution with mean of 8 and standard deviation of 2.5) of the first 10 consumers in mainstream and niche were set.

3 Competition and disruptive technology in social networks

3.1 Introduction

The notion of disruptive technology or innovation has received more attention and discussion within management literature and less 'popular' in that relating to economics. The notion of disruptive technology, subsequently generalized as disruptive innovation, was put forward by Clayton Christensen in his seminal work, "The Innovators' Dilemma", as part of his explanation of the superseding of well-managed companies by new entrants into the market. Incumbent companies, despite listening effectively to their important consumers, fail to maintain their success or respond to disruptive threats. Although this theory has attracted the attention of scholars and managers, it has also been subject to sharp criticism. Sood and Tellis (2010), for example, argued that the disruption resulting from 'lower attack', as suggested by this theory, is exaggerated. The term 'lower attack' refers to one by new entrants who offer products of sufficient quality at a lower price initially targeting low-end consumers and over time entering the mainstream segment. This disruption, indeed, occurred. However, over a period of 50 years across 36 different industries it occurred in only a small number of instances. Empirical evidence confirms that certain new and potentially disruptive technologies turned out to be severely so while others did not (Vaishnav, 2008; Keller and Hüsig, 2005). The explanation for such 'inconsistency' could be that of network effects, an important concept of technology competition propounded by Brian Arthur (1989). Due to network effects, consumers might remain loyal to an established technology, thereby continuing to represent its existing broad base. This trend might preventing a new and potentially disruptive technology being adopted and gaining wider currency.

Arthur (1989) explained that when two or more technologies compete, increasing returns on adoption render the adopted technology more familiar to users, it is then further improved, more widely adopted by other users and, eventually, creates lock-in. A number of studies that formalized disruptive technology theory largely failed to take network effects into account (Adner, 2002; Adner and Zemsky, 2005; Buchta et al., 2006; Mount, 2012). Vaishnav (2008) and Hüsig et al. (2009) addressed this issue empirically, suggesting that strong network effects might prevent disruption. One strong assumption that underlies technology competition with network effects is that every consumer is connected to every other individual in the population – in other words, constituting a complete network. This assumption leads to a lock-in outcome while, in reality, competing technologies can be observed to coexist within the market. Considering the fact that consumer decisions regarding technology adoption might be influenced to a great extent by a limited number of significant others, such as friends, colleagues, or family members, some softening of the complete network assumption by considering consumer network structures in complex networks appears advisable.

In the literature on technology diffusions in complex networks, some studies focused on the diffusion of a single technology (Abrahamson and Rosenkopf, 1997; Delre, et al., 2007; Delre, et al., 2010). These studies clearly showed how different consumer network structures affect the pattern and speed of diffusion as well as proposing how the number of network links and minor idiosyncrasies of the structures might result in large effects on innovation diffusion within the network. Certain studies address competition between two or more product technologies where these constitute rivals within the same mainstream segment (Janssen and Jager, 2001; Janssen and Jager, 2003; Lee, et al., 2003, Lee and Song, 2005). These studies basically communicate the same message, namely; ignoring consumer network structures in the domain of technology competition, especially when network effects are present, might yield misleading results. These scholars developed agent-based modelling and computer simulation in order to investigate the emergent competition outcomes resulting from micro-interactions between consumer-agents and between companies and consumer-agents.

Within the context of technology competition and market dynamics in complex networks, those studies focused on comparable technologies competing in the market. Investigation into a particular type of technology competition, such as that between new and potentially disruptive technologies versus established technologies in complex networks, remains to be conducted. Therefore, this paper tries to make good this shortfall, firstly, by discussing and mapping the competition dynamics and disruptive technology in social networks into a conceptual framework and, secondly, by elaborating how different consumer network structures influence the probability of technology disruption.

Technology disruption might itself contribute to addressing the notion of inescapable lock-in which is of great interest, spurring intense debate between numerous economists (e.g. Cantner and Vanuccini, 2016; Malerba, et al., 2007; Witt, 1997). The diffusion dynamics of new and potentially disruptive technology within complex networks, coupled with performance oversupply of established technology as well as the existence of segments with heterogeneous preferences (Christensen, 1997; Malerba et al., 2007) could, arguably, lead to the formation of critical mass (Witt, 1997). This process might subsequently increase the potential for disruption and, hence, contribute to the overcoming of lock-in. This study aims to shed light on how different topologies of consumer networks influence the probability of disruption and might eventually overcome lock-in.

3.2 Disruptive technology

Disruptive technology theory was advanced by Christensen in his famous 1997 book entitled “The Innovator’s Dilemma”. In this work, Christensen explained how incumbent companies, despite following best practice in terms of listening to consumer needs, fail to cope with new entrants offering innovative disruptive technology. According to Christensen, disruptive technologies are ones that provide different values from mainstream technologies and are initially inferior to mainstream technologies within the dimensions of performance that are most important to mainstream customers. Christensen introduces the concept of changing performance over time, plots the trajectories of product performance provided by companies and demanded by customers for different technologies and market segments, and shows that technology disruption occur when these trajectories intersect (Figure 3.1).

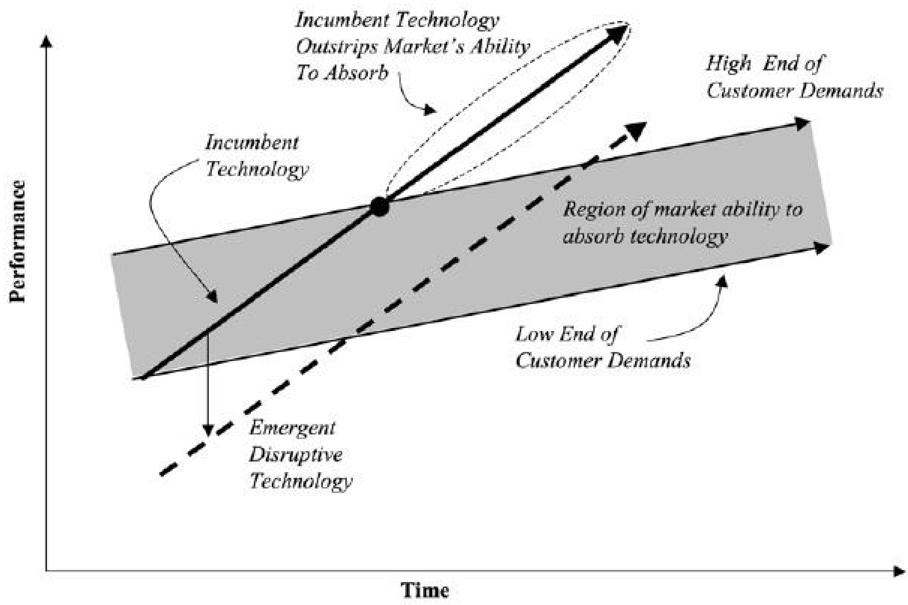

Figure 3.1 Disruptive technology model (Krikos, 2011)

Each product based on disruptive technology can, in its early stages, only serve a niche segment. Further development could raise the performance of disruptive technology to a level sufficient to satisfy mainstream customers. Although enhanced, the performance of disruptive technology remains inferior compared to that of established mainstream technology which is also constantly improving. Over time, due to an improvement rate more rapid than the market can absorb, the performance of mainstream technology will have exceeded the demand of mainstream customers and culminated in performance oversupply. Market disruption occurs when a new product incorporating disruptive technology displaces a mainstream product in a mainstream market enabled by a performance oversupply of mainstream technology and prompted by the lower price of new technology (Adner, 2002; Yu and Hang, 2009).

A heated debate has been provoked over the definition and scope of disruptive technology (Yu and Hang, 2009), with certain scholars supporting Christensen's theory of disruptive technology, while proposing their own somewhat contrasting views. Others criticized the vagueness of the concepts presented as well as the predictive power of the theory (Danneels, 2004; Markides, 2006, Govindarajan and Kopalle, 2006). Such commentators contributed a series of analyses intended to establish the reliability and validity of the disruptiveness scale, suggesting that disruptive innovation should (1) be inferior with regard to those attributes valued by mainstream customers (2) offer new value propositions to attract a new customer base or a more price-sensitive mainstream market (3) be sold at a lower price and (4) penetrate the market from niche to mainstream.

Since the mechanism of disruptive innovation is of particular interest, Christensen (1997) argued that two conditions drive a new technology or innovation from the low-end niche segment to eventually displace established technology in the mainstream section of the market. Firstly, the continuous improvement of new technology over time eventually renders it more attractive to consumers in the mainstream segment, albeit the lower end of that segment which demonstrates greater price sensitivity. Secondly, performance oversupply of established technology, in other words, performance improvements beyond consumer requirements, yields a diminishing marginal utility for consumers in mainstream segments (Adner, 2002; Christensen, 1997). This "diminishing marginal utility translates into decreasing willingness to pay" (Adner, 2002) while rendering the lower price of disruptive technology more attractive.

In this paper, it will be argued that, even when those conditions are satisfied there are at least two factors that might strongly influence the probability of disruption: (1) network effects (Arthur, 1989; Katz and Shapiro, 1992), and (2) how consumers are connected to each other within a social network or consumer network structure. Many modern technologies are characterized by network effects, therefore implying an increasing return on adoption for consumers (Hüsig, et al, 2005; Keller and Hüsig, 2009; Vaishnav, 2008). Network effects might influence the probability of disruption. Therefore, incorporating these into any discussion about disruption innovation is of considerable relevance. Furthermore, the manner in which consumers are connected to each other in a social network, where the adoption decision of an individual consumer is affected by the adoption by his/her associated significant others, might also play a salient role in the probability of disruption. The literature on the diffusion of innovation and technology competition in social networks provides a comprehensive overview of how consumer network structures should be considered when examining the probability of disruption.

In a quest to understand the influence of network effects and consumer network structures on the probability of disruption, network effects and complex networks, in addition to their relevance to disruptive technology theory, will be discussed.

3.3 Network effects

When two or more technologies compete, an increasing return on adoption creates positive feedback. In other words, more extensive adoption renders the technologies more familiar to users and enhances their performance (Arthur, 1989). This, in turn, induces consumers to further embrace such technologies, eventually creating customer lock-in. When two or more technologies compete for a market of potential adopters, an 'insignificant event' might favor one over the other(s), resulting in its extensive adoption, and eventually dominance - a winner-takes-all outcome. Arthur (1989) provided a dynamic model that shows how insignificant or random historical events influence the selection of the market outcome of multiple equilibria. Lock-in might result in an inefficiency problem in which the dominance of inefficient technology prevents an innovative and superior technology from entering the market.

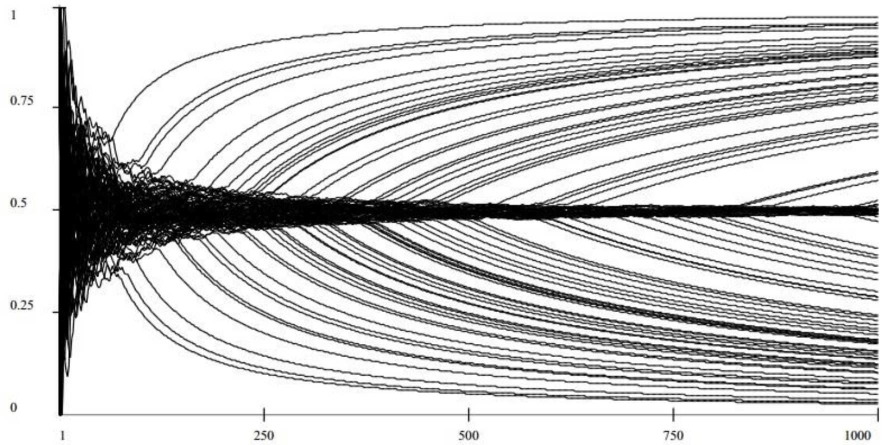

Figure 3.2 Simulation results of 500 runs from Arthur (1989)'s model. Source: Valente (2000)

Arthur (1989) suggested that consumers value a product or technology for two reasons, either the intrinsic preference of consumers (potential users) or the number of consumers who have already adopted the technology. In other words, the intrinsic preference and number of users determine the utility of a specific technology to new adopters. Arthur is particularly interested in the increasing returns on adoption where a technology's usefulness for new users increases in proportion to the number who have already adopted the technology (network effects). Network effects, as the result of increasing return on adoption, imply a winner-takes-all situation and lock-in as the probable consequences (Figure 3.2). This notion of lock-in has engendered heated debate among economists (Cantner and Vanuccini, 2016; Leydesdorff, 2000; Shurmer, 1993; Witt, 1997) some of whom have conducted theoretical and empirical studies challenging the notion of inescapable lock-in.

Srinivasan, et al. (2004) posited the important notion of the nature of network effects, asserting that it is not a matter of their being present or absent but, rather, one of degree. In their empirical study investigating the effect of network externalities on pioneer survival, these researchers employed a different group of raters composed of academic experts and managers to measure direct and indirect network effects of more than forty product technologies. They investigated product technologies with low network effects such as electric toothbrushes and pocket calculators and to produce technologies with very high network effects, such as fax machines and the operating systems of personal computers. They related the different degree of network effects of these technologies to the survival of a "pioneer", a term defined as the Firm which first introduced the corresponding technology to the market.

Theoretically, there are two ways in which network effects might influence one's acceptance of a certain technology. An individual accepts or rejects a technology when influenced by: (1) social relationships with other users, i.e. social influence, and (2) the total number of users of that technology in the market and the installed base (Pontiggia dan Virili, 2009). Social influence refers to the pressure from another person or group that influences the a potential user's decision of to accept or reject a technology, while the total number of consumers in the market induces an individual to accept a technology according to the benefit gained by adopting the technology with a large installed base.

As pointed out by Christensen (1997), a new and potentially disruptive technology is initially introduced within the niche with consumers harbouring different preferences for and appreciation of its simplicity, ease of use, convenience and affordability. The question is one of how new technology might gain a foothold in the niche, let alone challenge established technology in a mainstream market when that technology is characterized by network effects.

3.4 Disruptive technology and network effects

Despite many modern technologies being characterized by network effects (Hüsig et al, 2005; Keller and Hüsig, 2009; Vaishnav, 2008), any discussion of how these effects influence disruptive technology is absent from its original theory. Although this theory and its extensions (Adner, 2002; Govindarajan and Kopalle, 2006) explained how disruption is enabled by performance oversupply of established technology and is affected by the lower price of new potentially disruptive technology, strong network effects might hinder such disruption.

A number of empirical studies have addressed this issue and, indeed, have suggested that strong network effects might prevent disruption from occurring (Keller and Hüsig, 2009; Vaishnav, 2008). Keller and Hüsig (2009) in their work on developing an identification framework of disruptive innovation argued that, even if a potentially disruptive technology, such as a web application, might satisfy the performance requirement of consumers in a mainstream segment, because of network effects it is unlikely to pose a disruptive threat to established technology in the software industry. Vaishnav (2008) suggested that, while strong network effects can create a winner-takes-all market, weak network effects might favor the entrant. In other words, he argued that the strength of network effects might determine the outcome of the competition.

An interesting argument and empirical study result regarding the network effects presented by Shurmer (1993) is worthy of mention. He pointed out that, in most studies, network effects are assumed to be uniform across all consumers, going on to argue the heterogeneity of network effects across consumer groups. In his empirical study on software program applications, Shurmer showed that network effects vary between consumers since network effects are derived from different sources, e.g. training courses, books and adds-on to mention but a few. He further suggested that heterogeneity in network effects between consumers allow competing technologies to co-exist within the market, putting forward this theory of heterogeneity in network effects in an attempt to counter the notion of lock-in propounded by Arthur (1989).

One common assumption underlying theoretical and empirical studies in the literature on technology competition and network effects is that every consumer is connected to every other consumer within the population. This assumption leads to the notions of winner-takes-all and lock-in as suggested by Arthur (1989). Furthermore, it also leads to an overemphasis on the importance of an installed base. Lee and Song (2005) demonstrated how an unreasonable focus on installed bases could be misleading by highlighting the case of instant messaging (IM). IM was thought to be an example of lock-in. However, this subsequently turned out not to be the case. AOL built an installed base of more than 18 million users in 1999 when MSN and Yahoo had recently launched their instant messaging service. Despite expectations of AOL dominance, due to its installed base, MSN and Yahoo managed to narrow the gap and, in 2002, achieved a comparable number of unique visitors to that of AOL, the market leader. This case showed how taking network effects into account without considering network structures of consumers could mislead scholars and practitioners. Therefore, in this study, consumer network structures are taken into account during the discussion of the probability of disruptive technology with network effects. A review of social networks and their classifications which are relevant to this study is provided below.

3.5 Social networks

Networks are modeled by graphs, which consist of nodes and edges or links. Graphs can be categorized into: (1) complete graphs and (2) sparse graphs. A complete or fully-connected graph exists when every node within the network is connected to every other node. Technically speaking, this graph features one degree of separation or a path length of one. When a consumer connects with a smaller number of counterparts a sparse graph might constitute a more reasonable representation. Several ways of characterizing sparse graphs include; regular, random, small-world and scale-free (Watts and Strogatz, 1998; Barabasi and Albert, 1999; Amaral et al., 2000). Regular and random graphs can be classified as simple networks, whereas small-world and scale-free graphs are classified as complex varieties.

3.5.1 Simple networks

Simple networks consist of two contrasting network topologies, namely; regular and random. Regular network topology is a simple network coupled in geometrically regular ways where "many phenomena exhibit spatial order by obeying the rule of local, nearest neighbor interactions" (Lee, et al., 2006). In addition to its application in the field of physics, this regular network topology is applied to social phenomena. For example, Axelrod (1997) demonstrated that differences in beliefs and attitudes persist across groups by developing a model incorporating the assumption of a typical regular network. Although this topology approximates spatial phenomena where physical distance constrains social interactions, limitations exist on its ability to capture social distance which can violate the transitivity of distances (Barnett, 1989; Watts, 1999). This graph has the property of a high degree of clustering, meaning that individuals within the network share a substantial number of common acquaintances, such as in the case of users of corporate instant messaging. The other characteristic of regular graphs is that of long path length or a high degree of separation, since the structure tends to increase the number of steps required for one individual to reach any other individual within the network.

Random networks feature another simple network topology where any individual can be connected to any other in the world. The influence of physical distance matters little within random networks and, in the presence of such random connectivity, it requires only a few steps for each individual to reach every other individual (Erdös and Rényi, 1959). In other words, the network is characterized by a low degree of separation or short path length. The other characteristic of random networks is that of a low degree of clustering where individuals are unlikely to share common acquaintances since each individual randomly contacts strangers. Internet chat rooms might well belong to this type of network.

As pointed out by Watts and Strogatz (1998), real world networks lie somewhere between regular and random networks, a fact prompting a discussion of complex networks.

3.5.2 Complex networks

Watts and Strogatz (1998) put forth an idea how to deal with the complexity of the real network structure. The basic idea is that the complex network in this world lies between regular and random network. The initial idea of this network can be traced to Granovetter (1973, 1983) where he showed the important role of social bridge (or shortcuts) in job searches. He observed that individual's successful job searches are often done through contacts who are not close friends. He basically envisioned social networks as aggregate of clustered subgroups and 'social bridges' (shortcuts). It is Watts and Strogatz (1998) who formalized his idea into an algorithm that covers the range of possible topologies between regular and random network.

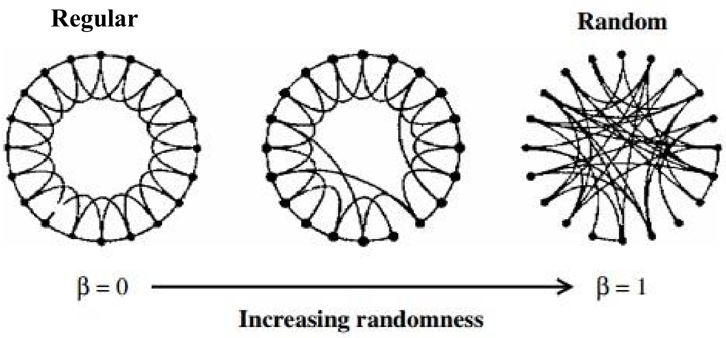

Figure 3.3 Watts-Strogatz small-world model (Source: Watts, 1999, p.68)

Lee et al. (2006) pointed out the three advantages of using this topology: (1) the absence of physical distance constraints on social interaction, (2) Watts and Strogatz's (WS) model allows researchers to examine the dynamics of complex network by adjusting only one parameter (β), namely; the availability of shortcuts or re-wiring probabilities and (3) this WS model represents the features of real world networks, i.e. high clustering and low degrees of separation. Nevertheless, the weaknesses of this model include: (1) a WS model assumes that networks are static and, hence, ignores their evolution and growth, (2) this model assumes that all ties or edges are equal, and (3) although the WS model, which can be approximated by Poisson distribution, draws support from empirical works in acquaintance networks (Amaral et al., 2000), it is not appropriate to describe them as real world networks where hubs exist.

Large networks, such as world-wide-web and scientific collaborations, have been analyzed, with node connectivity being found to follow a scale-free, power-law distribution (Barabási and Albert, 1999). This distribution might also describe the consumer networks since Rogers (1995) explained that early adopters of innovation are typically individuals with solid reputations and comprehensive contact networks. The generation of this scale-free graph, according to Barabási and Albert (1999) involves: (1) network growth over time through the addition of new nodes (2) new nodes' preference for links to nodes already possessing many connections (hubs), often referred to as preferential attachment. A newly-created webpage, for example, would be likely to create association with already well-connected webpages. Table 3.1 provides a simplified summary of networks classifications and their characteristics.

Table 3.1 Simplified summary of various network topologies and their corresponding characteristics, adapted from Lee et al. (2003)

Network typology			Example	Characteristics	Reference
Complete graph	fully-connected		family network	every node is connected to another nodes in the network	Arthur (1989)
Sparse graph	Simple network	regular lattice	instant (mobile) messaging	high degree of clustering, long path length	
		random	internet chat room	low degree of clustering, short path length	Erdös & Rényi (1960)
	Complex network	small-world	network of e-mail users	high clustering and short path length; important role of shortcuts (rewiring probabalities)	Watts & Strogatz (1998), Granovetter (1973)
		scale-free	world-wide-web	high clustering and short path length; important role of hubs; growth and preferential attachment properties	Albert, Jeong and Barabasi (1999)

3.6 Diffusion of innovation and competition in social networks

This paper presents an overview of the literature on innovation diffusion in complex networks to understand why certain network structures are more efficient for a diffusing novel technology than others. Understanding how new technology diffuses more effectively in certain network structures than others will, hopefully, allows us to relate them to the context of technology competition and the probability of disruption.

Firstly, a review of the diffusion of single innovations in complex networks is required. Notable works in this domain include those of Abrahamson and Rosenkopf (1997), Delre et al., (2006 and 2010) and Janssen and Jager (2003) in which agent-based modeling and computer simulation are widely employed. From the literature on innovation diffusion, it is understood how network structures influence its speed and pattern. Abrahamson and Rosenkopf (1997) proposed a theory that the number of network links and the minor idiosyncrasies of their structures can have profound effects on the degree of innovation diffusion among members of a social network. Delre et al. (2006) showed how the degree of randomness within a network influences the diffusion rate. Diffusion speed is low in regular networks, increases in small-world networks, but is again low in random networks. Since recent research has demonstrated that large networks are characterized by scale-free power-law distribution, Janssen and Jager (2003) investigated the role of hubs, a small number of consumers with connections, in market dynamic results. Their simulation results showed that hubs exert a significant influence on others' consumption behavior. Delre et al. (2010), who investigated the role and effects of hubs in innovation diffusion, concluded that their role across a range of markets can differ. Although hubs are acknowledged to impact significantly on many consumers, simulation results indicated that when hubs place limits on the maximum number of connections, innovation diffusion is severely hindered and the outcome is uncertain.

At that point, a number of works on the dynamics of technology competition in complex networks will be reviewed. Studies of how consumer network structures play a role in the competition between technologies, particularly their role in the incompatible entry of new technology when pre-existing technology has been established within the market or has dominated it (lock-in), have been identified within the literature (Janssen and Jager, 2001; Janssen and Jager, 2003; Lee et al., 2003; Lee and Song, 2005). The common findings of such studies confirmed the importance of consumer network structures within market dynamics or competitive outcomes. In investigating incompatible entry in small-world networks, Lee and Song (2005) highlighted the fact that the longer the degree of separation of consumer network structures, the easier incompatible entry becomes, suggesting that small-world networks featuring numerous shortcuts and random networks are unfavorable to new incompatible technology. Janssen and Jager (2001 and 2004) showed how different network structures, i.e. small-world and scale-free ones, together with psychological needs, exert an important influence on market dynamics. They argued that hubs, people with numerous contacts which characterize scale-free networks, have a profound impact on the consumption of other consumers.

Reich (2015) highlights the influence of network structures on the diffusion of new technology where individuals can discuss, coordinate and make joint decisions. Hence, the degree of connectedness or 'cohesiveness' matters. The term 'cohesiveness here is assumed to be identical to the concept of clustering. In other words, the more 'cohesive' the community, the higher the clustering of the network. Reich suggests that a cohesive community experiences a trade-off. On the one hand, it hinders diffusion by blocking the importing of new technology into the group. However, on the other hand, when group members act collectively during the adoption process, this 'cohesiveness' enables innovation to diffuse effectively. Reich concluded that for new technology with a high degree of network effects or externalities, where such technology requires a higher number of adopters before other potential counterparts become willing to adopt, cohesive groups enable diffusion.

The basic concept underpinning the above-mentioned studies is the importance of correctly interpreting the consumer network of technology in question. As highlighted by both Lee and Song (2005) and Reich (2015), when investigating instant messaging (IM) services, such as AOL, Microsoft and Yahoo, it appears, at first sight, that IM is similar to an e-mail or internet chat room where user benefit depends on the number of participants within the network. After careful consideration, they suggested that, in reality, this is not the case. Unlike e-mail or chat rooms, the IM network consists of friends, colleagues or relatives as exclusive members which prevents outsiders from joining. This suggests that IM consumer networks are characterized by long path length or a high degree of separation. Therefore, the role of an installed base is much less pronounced and provides room for new technologies to exist in niche sectors or even dominate the market.

In the context of technology competition and market dynamics in complex networks, previous studies focused on comparable technologies competing within the market. A particular form of technology competition, such as that between new, potentially disruptive technology and established varieties is still absent. Adner (2002), Buchta et al., (2006), Malerba et al., (2007) and Vaishnav (2008) addressed such competition dynamics and took network effects into account. However, they disregarded consumer network structures in their model. Therefore, this paper tries to compensate for that omission by discussing and mapping the competition dynamics and disruptive innovation within complex networks into a framework of thought.

3.7 Competition and disruptive technology in social networks

Table 3.2 shows the descriptive summary and the ‘map’ of disruptive technology in social networks. The probability of disruption will depend on the network topology of the society or community where the new, potentially disruptive technology diffuses. The characteristics of each network topology might facilitate or hinder the ability of such innovative technology to survive or even thrive. A careful examination of how a new, potentially disruptive technology with network effects diffuses within a certain topology of consumer networks, for instance, regular, small-world and random in nature, might explain why the technology is eventually successful or otherwise in displacing established technology.

The conjecture presented here suggests that a market consists of consumer networks characterized by high clustering and a relatively high degree of separation (long path length) that allows a new and potentially disruptive technology to survive even if strong network effects are present. New entrants or companies offering a novel and potentially disruptive technology should find a niche characterized by a high degree of connectivity to protect themselves from the influence of network effects of established technology in the mainstream market. The consumer network structure characterized by regular topology or small-world topology with few shortcuts might provide favorable conditions in which a new and potentially disruptive technology can survive. Once the new technology gains a foothold in the niche market, the next question is one of how new technology infiltrates the mainstream market. It is contended here that in consumer networks characterized by small-world network properties, new entrants should invest effort in forming shortcuts or become 'diffusion actors' coordinating and encouraging adoption which allows critical mass formation (Witt, 1997). Critical mass would allow the new, potentially disruptive technology to establish itself and, hence, increase the probability of technology disruption. This conjecture might complement the original theory of disruptive technology which suggests that it is enabled by (1) technology development, e.g., improved performance of new, potentially disruptive technology, and (2) performance oversupply of established technology, since the latter develops at a faster rate than the market can absorb and induces diminishing marginal utility of consumers in a mainstream market (Adner, 2002).

In short, the conjecture proposed in this study suggests that the diffusion dynamics of a new, potentially disruptive technology within social networks, coupled with the notion of performance oversupply of established technology, can be expected to yield a critical mass, thereby increasing the probability of technology disruption.

Table 3.2 Descriptions and conjecture of technology competition dynamics and the likelihood of disruption according to different network structures

Scenario	Network typology			Competition dynamics	Reference	Likelihood of disruption in each network structure (own conjecture)	Mechanism to increasing the likelihood of disruption (own conjecture)
new (potentially) disruptive technology comes into market which is occupied by established technology	Complete graph	fully-connected		Winner-takes-all, result in lock-in	Arthur (1989)	old established technology persist due to strong network effects	Entrants to find a niche with high degree of connectedness (high clustering) and long path length characteristics. Once new technology gain foothold in niche, focus to break into the mainstream by forming shortcuts or employing 'diffusion agents' (Witt, 1997) to facilitate the formation of critical mass. Critical mass coupled with performance oversupply of established technology might increase the likelihood of disruption
	Sparse graph	Simple network	regular lattic	high clustering and long path length facilitate new echnology to exist in niche	Janssen and Jager (2001, 2003), Reich (2015), Lee and Song (2003), Lee et al., (2006)	likely of competitive isolation - new technology stays in the niche	
			random	No clustering and short path length is in favor for old technology	Janssen and Jager (2001, 2003), Reich (2015), Lee and Song (2003), Lee et al., (2006)	old established technology persist due to strong network effects	
		Complex network	small-world (SW)	Lots of shortcuts is in favor of old tech (as in random graph). Few shortcuts (high clustering), might provide chance for new tech	Janssen and Jager (2001, 2003), Reich (2015), Lee and Song (2003), Lee et al., (2006)	number of shortcuts and degree of separation influence the likelihood of disruption	
			scale-free	Market is dominated by few products as in random or SW with lots of shortcuts, the role of hubs is important for diffusion	Janssen and Jager (2001, 2003); Lee and Song (2003)	important role of hubs in promoting new technology - hub's role might be important for the likelihood of disruption	

3.8 Overcoming lock-in and disruptive strategy

Arthur (1989) highlighted lock-in phenomenon as being a result of increasing return on adoption. His model and simulation showed how two technologies compete and that increasing return on adoption will eventually lead to awinner-takes-all situation where consumers are locked into one technology. Witt (1997) criticized the underlying assumptions of Arthur's model and argued that the existence of critical mass is crucial to overcoming lock-in. Witt (1997) further suggested that the coordinators of 'diffusion actors', such as marketing agencies, create critical mass or government action which allows critical mass to occur.

Assuming that consumers are locked into an established technology, the proposed conjecture of the previous section, i.e. creating critical mass and increasing the level of disruption through disruptive strategy coupled with forming shortcuts (diffusing actors) in small-world consumer networks, might also support the notion of overcoming lock-in.

3.9 Conclusion, implication, limitation and research agenda

3.9.1 Conclusion

This paper seeks to propose a theoretical contribution in addressing the gap in the literature on disruptive technology and network effects by incorporating consumer network structures and speculating on how these influence the probability of disruption. The better consumer network structures and their influence in this regard are understood, even when strong network effects are present, the greater will be the contribution to the discussion of overcoming lock-in by supporting Witt's notion of critical mass formation.

Drawing on the diffusion of innovation, technology competition and complex network literature, it is understood that the influence of consumer network structures on market dynamics and competitive outcome cannot be ignored. Summarizing the extensive literature, this paper provides a 'map' of different network structures and their relevance to technology competition and the probability of technology disruption. The 'map' clearly shows the importance of consumer network structures in determining the outcome of technology competition and, hence, the probability of technology disruption. From Christensen's perspective, this phenomenon involved a particular type of technology competition distinct from the technology competition models described in the literature previously reviewed. In other words, technology disruption refers to competition between a new and potentially disruptive technology characterized by inferior performance and affordability which is initially attractive to the niche segment and an established technology that dominates the mainstream segment, this study attempts to propose conjecture as to how a new and potentially disruptive technology might survive and eventually displace an established one.

The line of argument proposed in this study is that a new and potentially disruptive technology might enjoy greater prospects of survival in a market characterized by significant clustering and high degrees of separation (long path length), since these network characteristics are favorable to incompatible entry and to entrants forming a niche. Once the new potentially disruptive technology gains a foothold in the niche, new entrants or companies should invest effort in forming new shortcuts or 'diffusing actors' to disseminate information as well as coordinating adoption in an attempt to enter the mainstream segment. Otherwise, the new technology will remain isolated in niche. This endeavor, coupled with performance oversupply of established technology, might yield critical mass and increase the probability of disruption. The conjecture suggests that the diffusion dynamics of new and potentially disruptive technology in social networks, allied with the notion of performance oversupply of established technology can be expected to yield a critical mass and, in turn, increase the probability of technology disruption.

3.9.2 Implication and limitation

An enhanced understanding of how consumer network structures influence the potential for technology disruption might have policy implications. Ignoring the role of consumer network structures in assessing technology competition could result an overemphasis on the importance of an installed base. This was the case in the US when FCC issued a regulation to prevent AOL from adding certain features based on concerns that the Firm's installed base would lead to a monopoly in instant messaging. This restriction was then lifted when it turned out that Microsoft and other entrants had rapidly made up lost ground.

The qualitative and intuitive nature of the theoretical exercise contained in this paper, however, requires formalization into a mathematical model which constitutes a challenging but exciting task for any future research agenda. Furthermore, an agent-based model and simulation (ABMS) might also constitute a meaningful option for formalizing the abstraction presented in this paper. ABMS might conveniently capture consumer heterogeneity in terms of the minimum requirements of products' functional characteristics and preference heterogeneity as well as simulate the manner in which consumers are connected to each other within social networks in terms of varying degrees of connectedness and rewiring probabilities. The competitive outcomes, including technological disruption, might emerge as global emergent properties from both micro interaction between consumers and that between consumers and companies within the market.

Last but not least, the theoretical nature of this paper also demands empirical evidence to support the proposed conjecture of technology disruption in complex networks.

4 Acceptance of disruptive technologies with network effects: An empirical study on long distance call technologies in Germany and Indonesia

4.1 Introduction

Investigating consumer acceptance of disruptive technologies, as exemplified by the various devices used to run long distance calls, forms the focus of this research. Concentrating on this area is justified since the technologies involved exhibit network effects properties characterized by increasing return on adoption (Arthur, 1989; Katz and Shapiro, 1985), while disruption phenomena can also be observed. Previously, people had used fixed-line telephones to call their relatives and friends resident in other cities or countries. However, since the internet has become ubiquitous in nature, people have switched to internet telephony for this purpose and the fixed-line telephone has been replaced by Skype as the means of making a long distance call (York, 2013; Rao, et al., 2006). With regard to long distance calls, particularly international calls, analysis by TeleGeography confirms Skype's volume of international traffic as having increased dramatically with the result that it has superceded international fixed-line phone calls in popularity.

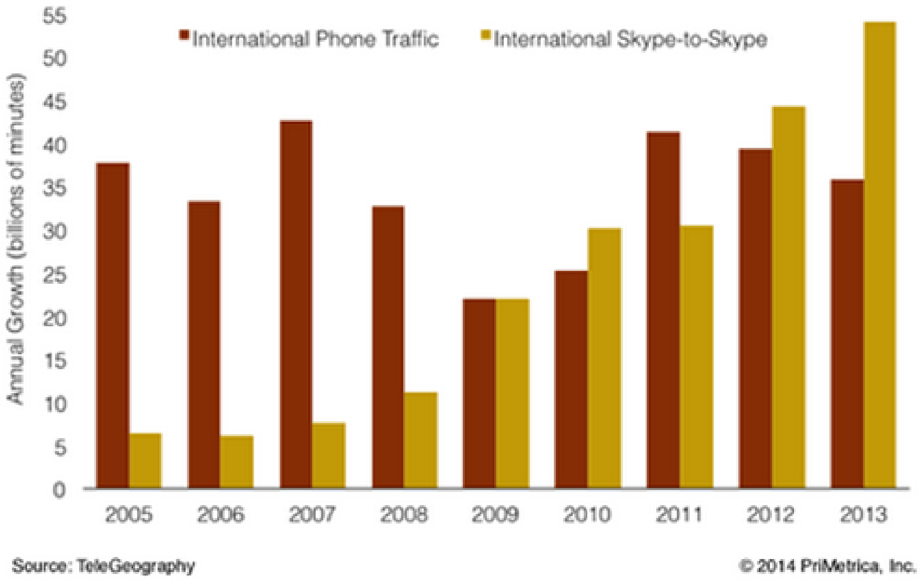

Figure 4.1 International phone and Skype traffic data from 2005 to 2013 (Source: Telegeography)

Figure 4.1 clearly shows the pattern of disruption of international fixed-line calls resulting from Skype's entry into the market. According to a London-based research Firm, Ovum, global telecommunication companies such as China Mobile, Deutsch Telekom and

Telefonica will lose a combined USD 386 billion between 2014 and 2018 due to consumers switching to internet telephony or over-the-top voice applications such as Skype, as reported on the Fortune website (2014)

More recent developments in mobile technology provide consumers with various program applications or apps making their lives easier. They include the apps for sending and receiving messages. The developers of these messaging-service apps, for example WhatsApp, Line, WeChat and Viber, have gradually added features, including voice and video calling facilities. Messaging-service apps have become very popular not only for instantly sending and receiving message, but also for making calls. Hence, the use of these apps might subsequently displace Skype for the purposes of making long-distance calls. As of February 2016, the number of active WhatsApp monthly users reached 1 billion worldwide compared to around 300 million for Skype (Statista, 2016).

Against this empirical background, it is interesting to identify what induces individuals to accept and employ new technology over an existing one and what constitute the underlying determinants of such acceptance - questions representing the central focus of this research. In seeking to address them, a new empirical approach in investigating the acceptance of technologies has been adopted. Firstly, technologies characterized by disruptiveness and network effects are assessed. Conceptually, disruptive technology theory, put forward by Christensen (1997), and network effects or network externalities theory propounded by Arthur (1989) are both referred to. Secondly, unlike most empirical studies of technology acceptance which investigate single technology or innovation, for instance, the adoption of internet banking (Lee, 2009; Amin, 2009; Pikkarainen, et al., 2004), mobile payment (Chen, 2008) and instant-messaging services (Wang et al, 2005), in this study three different technologies, albeit falling within the same category, are assessed. Thirdly, as a fundamental behavioral model underpinning the research, the theory of planned behavior (TPB) (Ajzen, 1991), properly extended to a model of technology adoption (TAM) (e.g. Davis et al., 1989), has been applied. Fourthly, rather than independently investigating the factors in technology acceptance, the variables underlying regression have been investigated comparatively. For example, the exploration of differences in actual use between internet telephony and fixed-line, contrasts in intention to use between messaging-service apps and fixed-line, among other issues, has been formulated.

Data relating to Germany and Indonesia was collected to enable a comparison of technology acceptance in different contexts, namely; developed and developing nations, to be made. The countries of origin of respondents were treated as a control variable. One conclusion is that the basic relations in the enhanced model of planned behavior finds support from the resulting data. In particular, how intentions positively and significantly influence actual device use, the mediative role of subjective norms that relate perceived usefulness to intentions and the mediative role of attitudes toward using that relate network effect variables to intentions are examined. Another finding is that historical lock-ins play a significant role. Germans demonstrate a greater attachment to fixed-line telephones and a more positive attitude and stronger commitment to their use, whereas Indonesians exhibit greater alacrity in adopting mobile-based messaging-service apps for long-distance calls.

Many modern technologies are characterized by disruptiveness and network effects. It is, therefore, hoped that the findings emerging from this empirical research will provide a valuable insight for telecommunication providers and app developers, as well as other companies working in technology, when developing their product technologies in both developed and developing countries. On the other hand, by understanding the factors determining user acceptance, telecommunications companies might obtain useful information in developing existing products that remain relevant and in anticipating the threat of disruption from new emerging technologies.

4.2 Theoretical background and framework

4.2.1 Disruptive technology and network effects

Since disruptive technology theory was first put forward by Christensen in 1997, many empirical and theoretical studies have followed. A number of scholars have either supported or criticised the theory (Danneels, 2004; Sood and Tellis, 2006), while other have tried to refine or develop it further (Adner, 2002; Govindarajan and Kopalle, 2006; Schmidt and Druehl, 2008). Most studies have addressed the behavior of incumbents in response to disruptive threats, or the lack thereof, from new entrants (Ahuja and Lampert, 2001; Paap and Kaatz, 2004). While the majority of investigations into disruptive innovation have focused on the supply side (Adner, 2002), an attempt has been made here to conduct empirical research on phenomenon from the demand side. The inclusion of network effects in the research is expected to provide valuable insight into how disruptive innovation is accepted and employed by consumers.

Disruptive technology is typically simple, convenient, easy to use and inexpensive. These features are more valued by niche or price-sensitive consumer segments, in contrast to mainstream customers who consider core characteristics, such as quality, speed, and capacity, to be of greater importance. The theory of disruptive technology was put forward by Christensen as long ago as the late 1990s. According to its author, such technologies are ones that produce different values to mainstream varieties and which are initially inferior to the latter with regard to those aspects of performance considered most important by mainstream customers. Christensen introduced the concepts of evolving performance over time, plotting Firm-supplied trajectories of product performance demanded by customers for different technologies and market segments, and demonstrating that technology disruption occurs when these trajectories intersect.

In its early stages, each disruptive technology-based product can only serve a niche segment. Further development can, potentially, enhance the performance of disruptive technology to a level sufficient to satisfy mainstream customers. Although improved, the performance of disruptive technology remains inferior compared to that of established mainstream varities which are also improving. Over time, the performance of mainstream or established technology will exceed mainstream customer demand, resulting in performance overshoot. Market disruption occurs when the new product (resulting from disruptive technology) displaces existing ones within the mainstream market (Yu and Hang, 2009).

When two or more technologies compete, the one ultimately adopted, even because of 'an insignificant random event', will become more familiar to users and improve further, leading to its wider adoption. The increasing return on take-up will eventually create lock-in (Arthur, 1989), a phenomenon known as network effects or network externalities. Katz and Shapiro (1985) also argued that network externalities exist when the utility that a user derives from a product increases with the number of other users of the same product. Pontiggia and Virili (2009) argued that empirical evidence confirming the influence of network effects on technology adoption is extremely limited and based on indirect approaches to measurement, such as the studies conducted by Schilling (2002) and Brynjolfsson and Kemerer (1996).

In order to understand how network effects might, in theory, influence technology acceptance, it is important to note that user decisions to accept or reject a specific technology are influenced by two factors: (1) social relationships with other users, or social effects/influences, and (2) the overall size of the market. On the one hand, "social effect" refers to personal or group pressure that may induce user acceptance of a particular technology. The construct of the "subjective norm" forming part of the Theory Acceptance Model propounded by Davis (1989) and the Theory of Planned Behavior postulated by Ajzen (1991) might capture this effect. In contrast, tmarket or user network effects induce an individual to accept a technology by increasing its user benefit due to the existence of a large installed base. As evidenced by the case of the acceptance of PC/Windows. Pontiglia and Virili (2009), in an attempt to provide empirical evidence of network effects on technology acceptance through experimentation, suggest that there are certain tasks significantly influenced by network size, including; transactional tasks, market-exchange tasks, communication tasks, learning tasks and secondary tasks. In this study, an attempt is made to capture both network effects, i.e. those resulting from social influence as well as others due to market or user network size.

4.2.2 Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM)

The Theory of Planned Behavior (TPB) has been covered extensively in the literature on information systems (Sentosa and Nikmat, 2012) and proven to be successful in explaining human behavior (Ajzen, 1991, 2002). The theory posits that the actual behavior of an individual in performing any action is directly affected by his or her behavioral intention. Subsequently, such intention is determined by that individual's attitude toward use, perceived behavioral control and subjective norm. According to Fishbein and Ajzen (2010), these three factors are determined by their respective beliefs; behavioral, control and normative. Those beliefs are, in turn, influenced by several background factors, including individual ones, for example, personality, mood, values; social factors, for instance, education, age, gender; and information factors, such as knowledge, media and intervention. In this study, rather than measuring behavioral, control and normative beliefs, an attempt has been made to decompose each factor determining behavioral intention to employ technology, namely; attitude toward use, subjective norms and perceived behavioral control, into several explanatory variables as previously attempted by Taylor and Todd (1995). In formulating the explanatory variables of attitude toward use, the concept underlying Technology Acceptance Model 2 or TAM2 (Venkatesh and Davis, 1989), where attitude toward use is directly influenced by perceived usefulness, was drawn upon. Certain variables positively related to perceived usefulness drawn from TAM2, i.e. perceived ease of use and image are employed. TAM is widely used in investigating the acceptance of modern technologies (Davis et al., 1989) and is appealing because it is parsimonious, specific and exhibits strong predictive power of technology use (Lee, 2008).

In this study, three pairs of contrasting technologies were assessed: first and second technology (fixed-line vs. internet telephony), first and third technology (fixed-line vs. messaging-service apps) and second and third technology (internet telephony vs. messaging-service apps) were compared. In this manner, the determinants of user acceptance of one technology over the other can, hopefully, be explained. The determinants of user acceptance of internet telephony over fixed-line, messaging-service apps over fixed-line, and messaging-service apps over internet telephony can be discerned. Variables for regression, the difference in the same construct between two competing technologies, e.g. contrasts in actual use between internet and fixed-line telephony and differences in intention to use between messaging-service apps and fixed-line telephony, among others, have been formulated. The Research Method section below contains further explanation as to how these variables were arrived at.

Individual intention to demonstrate a given behavior, for example, accepting or using a specific technology, is, in this case, a central factor in the theory of planned behavior (Ajzen, 1991). The stronger one's intention to accept or employ a particular product technology, the more likely one is to actually use it. Therefore, the following hypothesis can be formulated:

Hypothesis 1: Differences in intention to use will be positively and significantly related to the differences with actual use.

The main tenet of TPB (as the extension of the Theory of Reasoned Action or TRA first proposed by Fishbein and Ajzen, 1975) is that one's intention is a function of three factors: attitude toward use, subjective norms and perceived behavioral control. Referring to Ajzen (1991), one's attitude toward behavior is defined as "the degree to which a person arrives at a favorable or unfavorable evaluation or appraisal of the behavior in question”, while subjective norms refers to “the person’s perception that most people who are important to him or her think that he/she should or should not perform the behavior in question” (Fishbein and Ajzen, 1975). Perceived behavioral control refers to the beliefs regarding the presence or absence of factors potentially facilitating or impeding performance of the behavior (Ajzen, 1991). Within the context of investigating the difference between the intention to use one device as opposed to another, the following hypotheses are proposed:

Hypothesis 2a: Differences in attitude towards use will be positively related to differences in intention to use.

Hypothesis 2b: Differences in subjective norm will be positively related to differences in intention to use.

Hypothesis 2c: Differences in perceived behavioral control will be positively related to differences in intention to use.

Drawing on the body of psychology-related literature, Davis (1993) suggested that perceived usefulness has a significant positive effect on attitude toward use. In other words, attitude toward use mediates the positive relationship between perceived usefulness and intention to use. Therefore, the following hypothesis is put forward:

Hypothesis 3: Differences in attitude toward use mediates a positive relationship between the contrasts in perceived usefulness and the differences in intention to use.

Katz and Shapiro (1985) and Arthur (1989) developed the concept of network externalities or network effects in describing the phenomenon of how product utility is related to the number of users of that product (the installed base). The greater the extent to which a product is adopted, the more consumers become familiar with it and the greater its improvement, subsequently leading to more adopters (Arthur, 1989). The focus of this study is user perception of the number of adopters, rather than the actual number of users per se. It is argued that a subjective norm mediates the relationship between the perceived current number of users as well as the future number and their intention to use. This leads to the following hypotheses:

Hypothesis 4a: Differences in subjective norms mediate the positive relationship between the differences in the perceived current number of users and contrasts in intention to use.

Hypothesis 4b: Differences in subjective norms mediate the positive relationship between the differences in perceived future number of users and contrasts in intention to use.

The perceived number of existing users might encourage potential users’ intention to adopt new technology since they perceive its present and/or future, large, established base or large pool of adopters as likely to increase the sense of control in using the technology, e.g. when they have to overcome minor technical difficulties. In other words, perceived behavioral control mediates the effect of the perceived number of users on the intention to use. The following hypotheses are proposed:

Hypothesis 5a: Differences in perceived behavioral control mediates the positive relationship between the differences in perceived current number of users and the contrasts in intention to use.

Hypothesis 5b: Differences in perceived behavioral control mediate the positive relationship between the differences in the perceived future number of users and the contasts in intention to use.

The variable of technology utility propounded by Wang et al. (2005) which refers to standalone utility being unrelated to the number of users or user size (Farrel and Saloner, 1986) has been adopted. The manner in which differences in technology utility exerts an effect on the difference in perceived usefulness represents the focus of investigation. Therefore, the following hypothesis is put forward:

Hypothesis 6a: Difference in technology utility will be positively related to contrasts in perceived usefulness.

Davis (1993) argued that if a user assesses two systems with identical features, he/she should find the less complex one more useful. Given that the system is part of a user's overall job, the easier the system is to apply, the more productive a user becomes. Disruptive technologies are typically viewed to be simpler and easier to use (Tellis, 2006), despite the empirical data still being limited (Reinhardt and Gurtner, 2013). Hence, that concern is addressed by means of this empirical study which proposes the following hypothesis:

Hypothesis 6b: Differences in the perceived ease of use will be positively related to contrasts in perceived usefulness.

From a network effects perspective, the perceived number of current users is positively related to perceived usefulness, since the higher the number of people who use the same technology for long-distance calls, the greater the benefit or value they will obtain when making calls. The following hypothesis is, therefore, proposed:

Hypothesis 6c: Differences in perceived current number of users will be positively and related to contrasts in perceived usefulness.

Venkatesh and Davis (2000), citing Moore and Benbasat (1991), defined image as "the degree to which use of an innovation is perceived to enhance one's … status in one's social system." They further explained that the increased influence and power resulting from enhanced status will lead to improved performance and productivity, which is the definition of perceived usefulness. Against this background, the following hypothesis relating to differences in image and contrasts in perceived usefulness is put forward:

Hypothesis 6d: Differences in image will be positively related to the contrasts in perceived usefulness.

Since disruptive technologies typically characterized by their affordability have been investigated, it is believed to be important to include perceived affordability into the model. Referring to Völckner (2008), product price provokes two responses from consumers, namely; sacrifice and informational effects. If the sacrifice effect refers to the economic reason or rationale for consumers to spend money on acquiring a product, the informational effect is related to how they regard price as a quality indicator. In addition, consumers may infer certain "facts" about usefulness based on price information (Reinhardt and Gurtner, 2013). In this study, the cost a consumer bears to make long distance calls as perceived affordability, which refers to consumer perception of how "little" he/she pays to make this type of call, is considered. Since consumers will experience difficulty in determining the price per minute of calls using Skype or WhatsApp, in the questionnaire, respondents were provided with qualitative answer options ranging from 0 (low) to 6 (high) to capture as effectively as possible their perception of cost when making long-distance calls. It is hypothesized here that perceived affordability is related to perceived usefulness as follows:

Hypothesis 6e: Differences in perceived affordability will be related to contrasts in perceived usefulness.

4.3 Research model

Figure 4.2 depicts the hypothesized model into a structural diagram, where Δ stands for 'difference'.

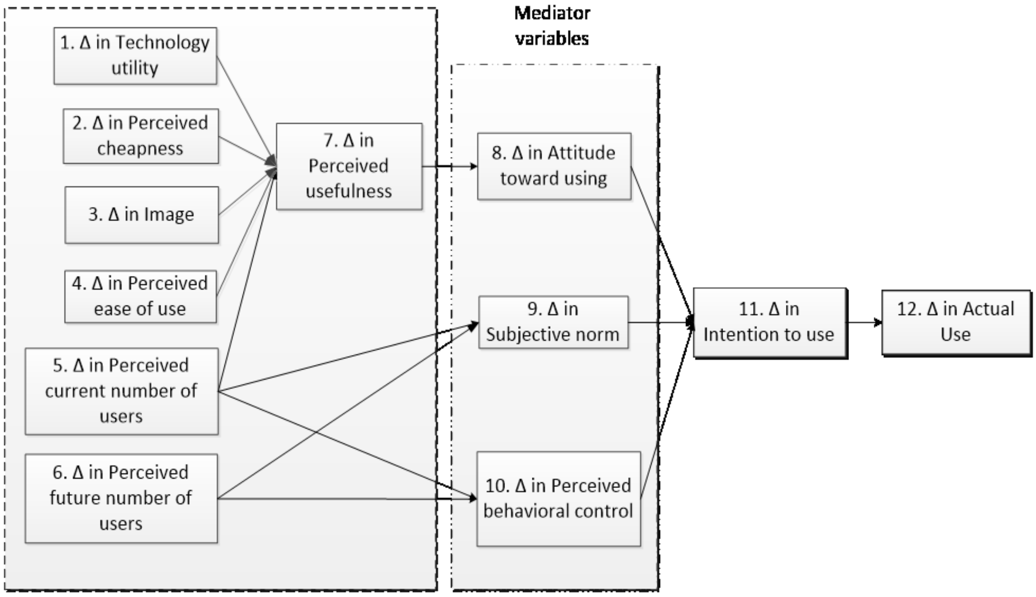

Figure 4.2 Proposed model to investigate the acceptance of disruptive technologies with network effects

In total, twelve variables have been employed. Actual Use, Intention to Use, Attitude towards Use, and Subjective Norm are the variables adopted from TPB and TAM since both theories employ the same constructs. Perceived Behavioral Control is adopted from TPB. Perceived Usefulness, Perceived Ease of Use, and Image are adopted from TAM2 (Venkatesh and Davis, 2000). Technology Utility and Perceived Current Number of Users are adapted from the work of Wang et al (2005) and Pontiggia and Virili (2009), whereas Perceived Future Number of Users constitutes the present author's proposed construct. Perceived Affordability is adapted from Reinhardt and Gurtner (2013). The explanation of every variable is provided in Table 4.1. For ease of presentation, abbreviations for every variable are used as shown in Table I in the following sections.

Table 4.1 List of variables in the model

Construct (Abbr.)	Definition	Reference
1. Δ in Technology Utility (dTUTIL)	Differences in a stand-alone utility which is unrelated to user or market size and used to describe utility not arising from the network effects	Farrel and Saloner (1986), Saloner and Shepard (1995), Wang et al. (2005)
2. Δ in Perceived Cheapne s (dPCHEAP)	Differences in the perception of cost that a person has to bear to use the system under investigation.	Reinhardt and Gurtner (2013)
3. Δ in Image (dIMAGE)	Differences in the degree to which use of an innovation is perceived as enhancing one's status in one's social system.	Venkatesh and Davis (2000)
4. Δ in Perceived Ease of Use (dPEoUSE)	Differences in the degree to which a user expects the use of system under investigation to be effort-free.	Davis (1989), Venkatesh and Davis (2000)
5. Δ in Perceived Current Number of Users (dPCUSER)	Differences in user perception of the current number of people adopting the system under investigation	Wang, et al (2005), Pontiggia and Virili (2009)
6. Δ in Perceived Future Number of Users (dPFUSER)	Differences in user perception of the future number of people adopting the system under investigation	Author-proposed construct
7. Δ in Perceived Usefulness (dPUSEFUL)	Differences in user subjective probability that using the system under investigation will increase his/her performance	Davis (1989), Venkatesh and Davis (2000)
8. Δ in Attitude Towards Using (dATU)	Differences in an individual's favorable or unfavorable assessment regarding the behavior in question, i.e. actual use of the system.	Ajzen (1991), Davis (1989)
9. Δ in Subjective Norm (dSNORM)	Differences in an individual's perception that most people who are important to him think that he/she should or should not demonstrate the behavior in question.	Ajzen (1991), Davis (1989), Venkatesh and Davis (2000)
10. Δ in Perceived Behavioral Control (dPBCONT)	Differences in an individual's perception of the ease or difficulty of implementing the behavior in question, in relation to the lack of skills or resources necessary to perform a particular task.	Ajzen (1991)

11. Δ in Intention to Use (dINTENT)	Differences in user's probability to use the system under investigation or a measure of the strength of one's willingness to exert effort while performing certain behavior (i.e., use the system).	Ajzen (1991), Davis (1989), Venkatesh and Davis (2000)
12. Δ in Actual Use (dACTUAL)	A variable to assess the differences in the degree of a person's use of the system under investigation.	Davis (1989), Venkatesh and Davis (2000)

4.4 Research method

In order to test the various hypotheses, data was collected from 480 individuals in Germany and Indonesia. An online questionnaire was set up and data was gathered through a combination of social media and a crowdsourcing platform. At the formulation stage, the questionnaire was assessed and reviewed by a professor of Economics, an associate professor, a post-doctoral student, and three PhD candidates personally known to the author. A pilot survey was conducted involving international postgraduate students attending masters degree courses at the author's university as a means of eliciting feedback on the length and format of the survey as well as the clarity of the questions. The initial questionnaire was produced in English, before being translated into German and Bahasa Indonesia.

4.4.1 Data collection and measurement development

The online questionnaire consisted of two sections. The questions in the first section were based on the variables as illustrated in the structural diagram contained in Figure 2. In this section, a seven-point Likert scale was employed, ranging from "strongly disagree" (0) to "strongly agree" (6) or "extremely unlikely" (0) to "extremely likely" (6). Every construct contained between two and four questions, with the exception of "perceived affordability". The second part comprised basic demographic questions including; gender, age, occupation, level of education and income. In this part, the extent of respondent access to the devices and apps under investigation, namely; fixed-line telephones, computers or laptop and smartphones, was also solicited. Last but not least, in this second part, respondents were asked whether they lived with family or independently (due to their family being resident in another city or country).

For every question or item, three different sets of answer options were provided, i.e. fixed-line, internet telephony and messaging service. An example of the questionnaire distributed is provided below:

1. I usually use [...] when I want to make a long-distance call ** fill [...] with corresponding technologies*

a. **Fixed-line telephone**	strongly disagree	o	o	o	o	o	o	o	strongly agree
b. **Internet telephony**	strongly disagree	o	o	o	o	o	o	o	strongly agree
c. **Messaging-service apps**	strongly disagree	o	o	o	o	o	o	o	strongly agree

2. How often do you use [...] in the last 30 days? ** fill [...] with corresponding technologies*

a. **Fixed-line telephone**	not at all	o	o	o	o	o	o	o	very frequently
b. **Internet telephony**	not at all	o	o	o	o	o	o	o	very frequently
c. **Messaging-service apps**	not at all	o	o	o	o	o	o	o	very frequently

Web-based or online Unipark® surveys in German and Bahasa Indonesia were devised, while social media (Facebook and LinkedIn) and crowdsourcing platforms were utilized as means of providing access to numerous and diverse participants in Germany and Indonesia. As argued by Gleibs (2016), crowdsourcing is widely used for participant recruitment in the social sciences due to the need for access to large and diverse samples, as well as that of avoiding over-reliance on students. The data was subsequently analyzed, the descriptive statistics calculated and a series of multiple regressions with Stata conducted.

4.4.2 Variables and specification strategy

Having eliciteddata relating to the acceptance of three distinct product technologies, it is possible to draw comparisons between two of them by identifying the difference in the mean value of each variable. For example, the difference in the mean value of actual use of internet telephony and that of actual use of fixed line lends itself to analysis. By subsequently taking the difference of the mean of the other variables, for example, intention to use and attitude toward use, twelve variables consisting of difference in actual use, difference in intention to use and others could be assessed.

The same procedure was repeated when a comparison was made between messaging- service apps and fixed-line telephones as well as messaging-service apps and internet telephony. All in all, three cases for regression exist: (1) internet telephony vs. fixed line, (2) messaging service apps vs. fixed line and (3) messaging service apps vs. internet telephony. Once again, twelve variables exist for each case.

4.5 Results

4.5.1 Sample profile

In total, 480 replies to the online questionnaire were collected from 210 German and 270 Indonesian respondents. Of these, 210 German and 150 Indonesian subjects participated by means of a crowdsourcing platform, i.e. CrowdFlower, while another 120 Indonesian respondents utilized social media (Facebook and LinkedIn).

The respondents consisted of 324 males and 111 females (with 45 prospective participants failing to reply). In terms of age composition: 17 were under 20 years old, 161 were aged from 20 to 30 years old, 117 were between 31 and 40 years old, while 88 fell within the 41-50 age range, with 51 being older than 50. With regard to educational level: respondents with a high school education numbered 73 (30 from Germany and 43 from Indonesia), 106 had a vocational study background (81 from Germany and 25 from Indonesia), 155 held a bachelors degree or equivalent (29 from Germany and 126 from Indonesia), 77 had obtained a masters degree or equivalent (44 from Germany and 33 from Indonesia), 7 held doctorates (4 from Germany and 3 from Indonesia), while 15 responded ‘Other’ or did not hold a university qualification.
In the Occupation category, a total of 428 responses were returned. 232 respondents were employees (124 from Germany, 108 from Indonesia), 67 were self-employed (19 from Germany and 48 from Indonesia), 53 were students (33 from Germany and 20 from Indonesia), 27 were entrepreneurs (2 from Germany and 25 from Indonesia), 18 worked in scientific fields or universities (2 from Germany and 16 from Indonesia), 11 were retired (10 from Germany and 1 from Indonesia), 14 had no job (8 from Germany and 6 from Indonesia), and 6 people answered ‘Other’ (for example, policemen and nurses). Information was also collected about marital status and income.

As a control variable, data was collected about subjects’ access to fixed-line telephone, computer or laptop and smartphone by means of the question: “How often do you have access to the [respective device]?” Response options included: (1) “always” (2) “sometimes” and (3) “never”. For access to fixed-line telephone; 228 (174 Germans and 54 Indonesians) answered “always”, 138 (19 Germans and 119 Indonesians) “sometimes” and 67 (10 Germans and 57 Indonesians) “never”. For access to computer or laptop; 233 (149 Germans and 84 Indonesians) replied “always”, 156 (35 Germans and 121 Indonesians) “sometimes”, and 42 (19 Germans and 23 Indonesians) “never. With regard to access to smartphone; 357 (166 Germans and 191 Indonesians) answered “always”, 53 (20 Germans and 33 Indonesians) “sometimes” and 24 (17 Germans and 7 Indonesians “never”. A complete demographic profile of respondents is available in Table 4.8 in Appendix.

4.5.2 Descriptive statistics

A stark contrast between Germany and Indonesia in terms of the actual use of long-distance call devices that might not empirically support the indication of disruption can be observed. To measure actual use, respondents were questioned in their respective languages, i.e. German and Bahasa Indonesia as follows: (1) I usually use […] when I want to make a long-distance call. The answer options were strongly disagree (0) to strongly agree (6); and (2) How often have you used […] in the last 30 days? The answer options were not at all (0) to very often (6). The parentheses […] were adjusted according to the product technology in question. The mean value of actual use was 2.77 for fixed-line, 3.06 for internet telephony and 4.24 for messaging service apps respectively, suggesting that messaging-service apps were most widely used. However, when actual use is identified according to the country of origin, it is evident that in Germany the mean value of fixed line is 3.65, internet telephony is 2.61 and messaging-service apps is 3.38. People in Germany are more attached to fixed-line use and resort to it most often for long-distance calls. In Indonesia, on the other hand, the mean value of fixed-line is 2.09, internet telephony is 3.4 and messaging service app is 4.91. These results confirm that Indonesians use messaging-service apps most frequently for long-distance calls.

Deeper analysis was achieved by means of a t-test to compare the mean of actual use between the two technologies and establish whether the difference between those two means is significant. For the overall sample, the difference between the mean value of internet telephony and fixed-line was positive and significant, suggesting the occurrence of disruption. The same result emerges for messaging-service apps versus fixed-line and messaging-service apps versus internet telephony. However, if a t-test is performed for the German sample alone, the result is negative and significant for internet telephony versus fixed-line. Moreover, the result is negative and not significant for messaging-service apps versus fixed line. This is interesting because it means that no evidence was found of disruption based on actual use, at least from the sample data obtained for Germany. Test results for the Indonesian sample, on the other hand, are similar to the overall sample. Country of origin is used as a control variable in the regression and its effect will be significant in the regression result section.

4.5.3 Factor analysis

Three datasets are used for the purposes of evaluation, namely; fixed-line telephone, internet telephony and messaging-service apps. For each dataset, the factor loading and reliability of the questionnaire were checked by means of Cronbach's α (CA). The criterion for reliability is an optimum CA score of 0.8 or, at the very least, 0.7 (Field, 2009; Nunnally and Bernstein, 1994).

For the fixed-line telephone dataset, all variables demonstrated an acceptable level of loading and a CA located within the range of 0.7 to 0.9, except for perceived behavioral control (PBC) which recorded a CA score of 0.57. The exclusion of item 3 in PBC serves to improve the CA score to the minimum acceptable level of 0.7. For the internet telephony dataset, all variables had an acceptable CA score, except for the subjective norm, whose CA score was 0.64 (further improved to 0.77 after the exclusion of item 2), and the perceived behavioral control variable with a CA score of 0.48 (increased to 0.57 after the exclusion of item 3). In the messaging-service apps dataset, the same problem of subjective norm and perceived behavioral control variable existed. Nevertheless, the subjective norm demonstrated an improved CA score of 0.7 after the removal of item 2, while the perceived behavioral control showed an enhanced CA score of 0.55 after the removal of item 3. The author is aware of this reliability problem, especially with regard to perceived behavioral control, and remains cautious while retaining these variables for further analysis. The table of CA scores and factor loading is available in the Appendix in Tables 4.12, 4.13 and 4.14 respectively.

The correlation matrix of variables of internet telephony vs. fixed line, messaging-service apps vs. fixed-line and messaging-service apps vs. internet telephony are shown in Tables 4.9, 4.10 and 4.11 respectively in the Appendix.

4.5.4 Regression results

The hypotheses were tested using a series of multiple regression models run from left to right (see structural diagram in Figure 4.2). The fundamental ingredient of the TAM and TPB approach, namely; the perceived usefulness of technologies, represented the starting point. The results of the first regression in the differences in perceived usefulness as dependent variables for internet telephony vs. fixed-line, messaging-service apps vs. fixed-line and messaging-service apps vs. internet telephony respectively are provided in Table 4.2.

Hypothesis 6a stated that differences in technology utility (dTUTIL) would relate positively to differences in perceived usefulness (dPUSEFUL). As expected, dTUTIL is positively and significantly related to dPUSEFUL ($p < .001$) in all three cases. Thus, Hypothesis 6a was supported.

Hypothesis 6b stated that differences in perceived ease of use (dPEoUSE) would relate positively to differences in perceived usefulness (dPUSEFUL). Furthermore, as expected, dPEoUSE is positively and significantly related to dPUSEFUL ($p < .001$) in all three cases. Thus, Hypothesis 6b was supported.

Hypothesis 6c stated that differences in the perceived current number of users (dPCUSER) would relate positively to those in perceived usefulness (dPUSEFUL). In the case of internet telephony vs. fixed-line and messaging-service apps vs. fixed-line, dPCUSER is positively and significantly related to dPUSEFUL ($p < .001$). Therefore, Hypothesis 6c is supported in these two cases. However, with regard to messaging-service apps vs. internet telephony, dPCUSER is not significantly related to dPUSEFUL.

Hence, Hypothesis 6c was not supported in this case.

Hypotheses 6d and 6e (differences in image and perceived affordability would relate positively to differences in perceived usefulness) were not supported for all cases because the relationships were not significant. Therefore, a modification of the model and a test of the new relationships as follows: differences in perceived affordability (dPCHEAP) would relate positively to differences in attitude towards use (dATU) and differences in image (dIMAGE) would relate positively to differences in subjective norm (dSNORM), was required.

A series of regressions with dATU, dSNORM and differences in perceived behavioral control (dPBCONT) as dependent variables was run. Subsequently, a regression with these three variables as independent variables and the differences in intention to use (dINTENT) as a dependent variable was conducted. The respective regressions and results for all three cases are shown in Tables 4.3, 4.4 and 4.5 respectively.

Table 4.2 Regression results (DV is the difference in perceived usefulness)

DV: Differences in perceived usefulness (dPUSEFUL)	Internet telephony vs. Fixed-line	Messaging-service vs. Fixed-line	Messaging-service vs. Internet telephony
	Coef.	Coef.	Coef.
Differences in technology utility (dTUTIL)	0.19 ***	0.31 ***	0.31 ***
Differences in perceived ease of use (dPEoUSE)	0.58 ***	0.13 ***	0.72 ***
Differences in perceived current number of users (dPCUSER)	0.16 ***	0.56 ***	0.05
Differences in image (dIMAGE)	0.07	0.00	0.08
Differences in perceived cheapness (dPCHEAP)	0.00	-0.03	-0.02
Gender	-0.14	-0.08	0.00
Country of origin	-0.03	0.36 *	0.32 **
Full access to fixed-line	-0.58 ***	-0.50 **	-
Full access to computer	0.07	-	0.04
Full access to smartphone	-	0.30	-0.01
Family live in other city	0.01	0.03	0.04
Family live in other country	0.44 *	0.55 *	0.04
_cons	0.26	-0.44 *	-0.42 **
F value	132.19	162.64	83.71
R^2	0.78	0.81	0.69
Adjusted R^2	0.77	0.80	0.68

*** p < .001, ** p < .01, * p < .05

Table 4.3 Regression results (DV is the difference in attitude towards using)

DV: Differences in attitude toward using (dATU)	Internet telephony vs. Fixed-line	Messaging-service vs. Fixed-line	Messaging-service vs. Internet telephony
	Coef.	Coef.	Coef.
Differences in perceived usefulness (dPUSEFUL)	0.68 ***	0.74 ***	0.64 ***
Differences in perveived cheapness (dPCHEAP)	0.26 ***	0.25 ***	0.10 *
Gender	0.02	-0.03	-0.03
Country of origin	-0.32	-0.57 **	0.02
Full access to fixed-line	-0.05	-0.07	-
Full access to computer	0.09	-	0.19
Full access to smartphone	-	0.24	-0.13
Family live in other city	0.26 *	0.20	-0.03
Family live in other country	0.00	-0.09	-0.06
_cons	0.05	-0.04	-0.13
F value	92.06	110.92	58.06
R^2	0.64	0.68	0.52
Adjusted R^2	0.63	0.67	0.52

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 4.4 Regression results (DV is the difference in subjective norm)

DV: Differences in subjective norm (dSNORM)	Internet telephony vs. Fixed-line	Messaging-service vs. Fixed-line	Messaging-service vs. Internet telephony
	Coef.	Coef.	Coef.
Differences in perceived current number of users (dPCUSER)	0.40 ***	0.36 ***	0.36 ***
Differences in perceived future number of users (dPFUSER)	0.15 ***	0.28 ***	0.29 ***
Differences in image (dIMAGE)	0.32 ***	0.17 **	0.26 ***
Gender	0.16	0.06	-0.12
Country of origin	0.76 ***	1.07 ***	0.30 **
Full access to fixed-line	-0.28	-0.27	-
Full access to computer	0.55 ***	-	-0.31 **
Full access to smartphone	-	0.73 ***	0.29 *
Family live in other city	0.10	0.14	0.03
Family live in other country	0.40	0.54	0.05
_cons	-0.80 ***	-1.32 ***	-0.33 *
F value	85.52	86.01	52.05
R^2	0.65	0.65	0.53
Adjusted R^2	0.64	0.64	0.52

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 4.5 Regression results (DV is the difference in perceived behavioral control)

DV: Differences in perceived behavioral control (dPBCONT)	Internet telephony vs. Fixed-line	Messaging-service vs. Fixed-line	Messaging-service vs. Internet telephony
	Coef.	Coef.	Coef.
Differences in perceived current number of users (dPCUSER)	0.29 ***	0.23 ***	0.19 ***
Differences in perceived future number of users (dPFUSER)	0.07	0.04	0.02
Gender	-0.03	-0.03	-0.01
Country of origin	0.50 **	0.58 **	0.09
Full access to fixed-line	-0.49 **	-0.59 **	-
Full access to computer	0.32 *	-	-0.32 **
Full access to smartphone	-	0.83 ***	0.56 ***
Family live in other city	-0.03	0.02	0.03
Family live in other country	-0.06	-0.05	-0.09
_cons	-0.32	-0.71 **	-0.30 *
F value	15.56	32.75	15.56
R^2	0.23	0.38	0.23
Adjusted R^2	0.21	0.37	0.21

*** $p < .001$, ** $p < .01$, * $p < .05$

To test the hypotheses about mediation, a regression with differences in intention to use (dINTENT) as a dependent variable and the differences in attitude toward use (dATU), differences in subjective norm (dSNORM) and differences in perceived behavioral control (dPBCONT) as an independent variable was also run. The results are shown in Table 4.6.

Hypotheses 2a states that dATU will be positively related to dINTENT. For all three cases, dATU is positively and significantly related to dINTENT. Therefore, Hypothesis 2a is supported by the data. Hypothesis 2b states that dSNORM would be positively related to dINTENT. For the first case of internet telephony vs. fixed line, dSNORM is positively and significantly related to dINTENT. The third case of messaging-service apps vs. internet telephony shows that dSNORM has a positive but weakly significant relationship with dINTENT. Hence, Hypothesis 2b is supported for the first and third case. However, dSNORM is positively but not significantly, related to dINTENT in the case of messaging-service apps vs. fixed-line. Therefore, Hypothesis 2b is not supported for the second case. Hypothesis 2c stated that dPBCONT is positively related to dINTENT. For all three cases, the regression result shows that dPBCONT is not significantly related to dINTENT. Therefore, Hypothesis 2c is not supported.

To test our hypotheses about mediation, the results contained in Tables IV, V, VI and VII can be used. Hypothesis 3 averred that dATU mediates the positive relationship between dPUSEFUL and dINTENT. For all cases, dPUSEFUL is positively and significantly related to dATU and the latter is, in turn, similarly related to dINTENT. Thus, Hypothesis 3 is supported. It is also supported by the Sobel-Goodman mediation test result, where the mediation effect of dATU was statistically significant with approximately 33% of the total effect (of dPUSEFUL on dINTENT) being mediated for internet telephony vs. fixed-line case. The case of messaging-service vs. fixed-line, as well as messaging service vs. internet telephony, yielded the equivalent results of 34% and 35% respectively.

Hypotheses 4a and 4b states that dSNORM mediates the positive relationship between differences in the perceived current number of users (dPCUSER), as well as the perceived future number of users (dPFUSER) and the dINTENT. In the case of internet telephony vs. fixed line, dPCUSER as well as dPFUSER both positively and significantly relate to dSNORM ($p < .001$). Subsequently, dSNORM also positively and significantly relates to dINTENT ($p < .01$). Thus, for the case of internet telephony vs. fixed line, Hypotheses 4a and 4b are supported. This result is also confirmed by a Sobel-Goodman mediation test. The mediation effect of dSNORM was statistically significant at approximately 53% and 55% of the total effect of dPCUSER, as well as dPFUSER, on dINTENT, respectively being mediated. In the case of messaging-service vs. fixed line, although both dPCUSER and dPFUSER were positively and significantly related to dSNORM ($p < .001$), the relationship between dSNORM and dINTENT was not significant. Hence, in the case of messaging-service vs. fixed line, Hypotheses 4a and 4b were not supported. With regard to messaging service apps vs. internet telephony, dPCUSER and dPFUSER were both positively and significantly related to dSNORM ($p < .001$). Subsequently, dSNORM also related positively and significantly to dINTENT ($p < .05$). Thus, in the case of messaging service apps vs. internet telephony, Hypotheses 4a and 4b were supported. This result was also supported by a Sobel- Goodman mediation test, where the mediation effect of dSNORM a¥z was statistically significant with approximately 49% and 55% of the total effect (of dPCUSER and dPFUSER respectively on dINTENT) being mediated.

Hypotheses 5a and 5b stated that the differences in perceived behavioral control (dPBCONT) mediate the positive relation between dPCUSER, dPFUSER and dINTENT. In all cases, the relations of dPBCONT were not significant to dINTENT. Therefore, Hypotheses 5a and 5b were not supported in all three cases.

Finally, with regard to Hypothesis 1 stating that the dINTENT would relate positively to difference in actual use (dACTUAL), as shown in Table 4.7, in all three cases as expected, dINTENT positively and significantly related to dACTUAL ($p < .001$). Therefore, Hypothesis 1 was supported in all cases.

Table 4.6 Regression results (DV is the difference in intention to use)

DV: Differences in intention to use (dINTENT)	Internet telephony vs. Fixed-line Coef.	Messaging-service vs. Fixed-line Coef.	Messaging-service vs. Internet telephony Coef.
Differences in attitude towards using (dATU)	0.79 ***	0.88 ***	1.11 ***
Differences in subjective norm (dSNORM)	0.40 **	0.32	0.43 *
Differences in perceived behavioral control (dPBCONT)	0.56	0.48	0.04
Gender	-0.11	0.05	0.08
Country of origin	-0.26	-0.12	-0.15
Full access to fixed-line	0.00	0.14	-
Full access to computer	-0.16	-	0.04
Full access to smartphone	-	-0.46	0.07
Family live in other city	0.07	-0.03	-0.11
Family live in other country	0.39	0.65	0.14
_cons	0.17	0.35	0.11
F value	132.62	125.73	58.32
R^2	0.74	0.73	0.56
Adjusted R^2	0.73	0.72	0.55

*** $p < .001$, ** $p < .01$, * $p < .05$

4.6 Discussion

4.6.1 Results

Differences in intention to use are positively and significantly related to differences in actual use. These results are consistent for all three cases and, hence, provide support for TAM and TPB frameworks.

As expected, the mediation effect of the difference in attitude towards using (dATU) on the positive effect of perceived usefulness (dPUSEFUL) towards difference in intention to use (dINTENT) was shown in all three cases. Variable dATU had the largest influence on dINTENT in all cases, which was subsequently explained by the dPUSEFUL. Nevertheless, differences were found in which a determinant predicts the dPUSEFUL most effectively among the three cases, as indicated by the determinant with the largest positive coefficient. For internet telephony vs. fixed-line and messaging-service apps vs. internet telephony, it was the differences in perceived ease of use (dPEoUSE) which most clearly explained the differences in dPUSEFUL. While in the case of messaging-service apps vs. fixed-line, differences in perceived current numbers of users (dPCUSER) exerts the largest impact on dPUSEFUL. For messaging-service apps vs. internet telephony, dPCUSER is not significantly related to dPUSEFUL, but it was indirectly related to dINTENT through differences in subjective norm (dSNORM). The determinant having the largest effect on dPUSEFUL was dPEoUSE.

The mediation effect of difference in subjective norm (dSNORM) was found to be supported by the data. However, the fact that this is not the case for messaging-service apps vs. fixed-line, due to the insignificant relationship between dSNORM and dINTENT is somewhat puzzling. It is understood that subjective norm refers to the perceived social pressure to perform a specific behavior or not (Ajzen, 1991). The intention to use a messaging-service over the intention to use fixed-line might be sufficiently explained by the differences in attitude towards using (dATU), which is influenced by dPUSEFUL and dPCHEAP. Variable dPUSEFUL in case of messaging-service vs. fixed-line is very strongly influenced by network-effect related constructs of the perceived current number of users (dPCUSER) ($\beta = 0.62$, $p < .001$). It might be possible to say that the differences in intention to use WhatsApp over fixed-line is mainly influenced by the differences in the perceived current number of users, rather than social pressure from other persons or group.

The mediation effect of differences in perceived behavioral control (dPBCONT) is consistently absent in all three cases since dPBCONT is not significantly related to dINTENT. The possible explanation for this is that making long distance calls and operating telecommunication devices such as fixed-line telephone, Skype or a messaging-service app is such a straightforward task that it requires a very limited degree of control or effort to perform. Therefore, it might be the case that perceived behavioral control becomes less relevant. Previous empirical research examining the effect of perceived behavioral control on behavioral intention has yielded mixed results. It has been found to be significant in several empirical studies, such as those predicting electronic toll collection service adoption (Chen et al., 2007), analyzing the acceptance of green products (Chen and Hung, 2016) and predicting pregnant women's intention to engage in regular exercise (Lee, et al., 2016).

It was also found that differences in image are not significantly related to those in perceived usefulness as hypothesized but, instead, it is positively and significantly related to differences in subjective norms for all cases. Venkatesh and Davis (2000) argued that image has a positive effect on perceived usefulness because one's enhanced status within a group should lead to improved job performance. Moreover, these researchers put forth that argument within the context of the adoption and application of IT systems in a work place. However, this hypothesis is not supported by the empirical data elicited. It appears that the differences in context matter within this specific context. The actual behavior of selecting and employing a device or app for long-distance calls is more personal where one's enhanced status has no significance to the 'performance' in making a long-distance call. It was found, instead, that it is positively and significantly related to differences in subjective norms.

Table 4.7 Regression results (DV is the difference in actual use)

DV: Differences in actual use (dACTUAL)	Internet telephony vs. Fixed-line	Messaging-service vs. Fixed-line	Messaging-service vs. Internet telephony
	Coef.	Coef.	Coef.
Differences in intention to use (dINTENT)	0.65 ***	0.69 ***	0.86 ***
Gender	-0.31	-0.24	0.05
Country of origin	0.73 **	0.51 *	-0.19
Full access to fixed-line	-0.95 **	-0.94	-
Full access to computer	0.71 **	-	-0.42 *
Full access to smartphone	-	1.44	0.82 **
Family live in other city	0.23	0.36	0.19
Family live in other country	0.86 *	0.26	-0.48
_cons	-1.00 **	-0.79 *	0.54 *
F value	81.42	109.13	45.94
R^2	0.57	0.64	0.43
Adjusted R^2	0.57	0.64	0.42

*** p < .001, ** p < .01, * p < .05

It is proposed here that differences in perceived future number of users (dPFUSER) will be indirectly related to perceived intention to use (dINTENT) through differences in subjective norm (dSNORM) and perceived behavioral control (dPBCONT). The results were found to be mixed. For the case of internet telephony vs. fixed-line, dPFUSER is positively and significantly related to dSNORM, but not to dPBCONT. dSNORM is positively and significantly related to dINTENT. Therefore, dPFUSER is indirectly related to dINTENT through dSNORM, whereas in the case of messaging-service vs. fixed-line, dPFUSER is positively and significantly related to dSNORM, but dSNORM is not significantly related to dINTENT. Hence, dPFUSER is not related, even indirectly, to dINTENT. The case of messaging-service apps vs. internet telephony showed that dPFUSER is indirectly related to dINTENT through dSNORM.

The actual use of fixed-lines in Germany is worthy of mention here. It was surprising that the mean of actual use of fixed line telephones is higher than the actual use of internet telephony and messaging-service apps, despite the global trend of disruption in long-distance calls. Possible explanations for this phenomenon are: (1) a high degree of fixed-line availability. From the data, we found that 85.7% of Germans enjoy consistent access to fixed-lines compared to 23.5% of Indonesians, and (2) Germans perceive fixed-lines to be relatively economical for long-distance calls. The data confirms that Germans' perceived affordability of mean-value of fixed-line was 3.09 compared to 1.4 for Indonesians (the higher the value, the more affordable the means of communication is perceived to be). The regression in Table 4.7 also confirms the relationship between the difference in intention to use and actual use since the country of origin as the dummy control variable (value=0 for the German sample and 1 for the Indonesian sample) is positive and significant in the first and second cases. It means that being Indonesian is positively and significantly related to the positive differences in the actual use of internet telephony and messaging-service apps vs. fixed-line. Attempts were also made to check whether country of origin moderates the relationship between the intention to use and actual use of fixed-line telephones. However, no significance in the interaction between intention to use and country of origin was identified.

As an illustration, the Appendix contains structural diagrams of the relationships between variables as the result of regressions in all three cases under investigation (Figure 4.3, 4.4 and 4.5).

4.6.2 Limitations

Although this study provides a new empirical approach in technology acceptance research and insights into the context of developed and developing country, certain limitations are highlighted. Given the nature of cross-sectional research, the findings of this study provide only a limited causal interpretation.

Particular types of product technology, i.e. those relating to long-distance calls were investigated. As with any telecommunication sector product technology, they were understood to exhibit strong network effects since the utility for a potential userthat can be derived from the products is enhanced as the number of users increases. Caution should be exercised in not generalizing the results of this study to include product technologies with distinct characteristics. Therefore, the study should ideally be followed up with an investigation into product technologies possessing different characteristics in terms of disruptiveness and network effects in order to understand how the determinants of technology acceptance might differ. For example, conducting a study of technology acceptance of product technologies in various music formats, e.g., compact disc, MP3 and music streaming, which certainly exhibit weak network effects, at least weaker than technologies in long-distance calls, is currently under consideration.

The results reported here might shed light on the acceptance of long-distance calls technology in different contexts, i.e. Germany as a developed country in contrast to Indonesia as a developing one. However, the results can certainly not be generalized to include other developed and developing countries. Therefore, similar studies need to be conducted in a range of countries as a means of developing a more general view on the acceptance of technologies or product technologies characterized by their disruptiveness and network effects, especially in the area of long-distance call technologies.

4.6.3 Implications

This study confirms that network effects influence the acceptance of new technology over an established one through subjective norm or social pressure from groups and close associates, as well as through perceived current and future number of users, albeit to a different extent.

Since differences in the perceived number of users has an indirect but significant and positive effect on contrasts in intention to use, it is important for providers or developers of internet telephony services as well as messaging-services apps to launch a strategy to rapidly secure a large installed base. Particularly in developing countries, where fixed-line telecommunication infrastructures are not well-developed and fixed-line services are neither widely available nor relatively inexpensive, internet telephony and messaging-service apps or internet and mobile application in general might be employed by mainstream consumers. The advancement in internet and mobile technology on the one hand and individuals' alacrity to accept internet and mobile apps on the other can be seen as the opportunity for the Indonesian government to provide telecommunications access for its people.

In a developed country such as Germany, it would appear that internet telephony and messaging-service apps are adopted more as complementary tools of well-established fixed-line telephones enabling people to make a long-distance call when they so wish. From this empirical finding, it might prove feasible to observe how fixed-lines exhibit strong network effects preventing new technology from taking over, and to infer that the same product technology might exert different degrees of network effects depending on the context.

Differences in perceived ease of use were found to be positively and significantly related to contrasts in perceived usefulness for all cases. Furthermore, differences in perceived affordability was found to be positively and significantly related to contrasts in attitude toward use in all cases. This confirms the notion of disruptive technologies which constitute ones that are typically simple, convenient, easy to use and inexpensive (Govindarajan and Kopalle, 2006). This result might imply that innovators and apps developers working within the telecommunications industry have to keep ease of use and affordability at the forefront of their minds when developing products and services.

Differences in perceived ease of use is found to be positively and significantly related to differences in perceived usefulness for all cases. Also, differences in perceived cheapness is found to be positively and significantly related to differences in attitude toward using in all cases. This confirms the notion of disruptive technologies which is technologies that typically simple, convenient, easy to use and inexpensive (Govindarajan and Kopalle, 2006). This result might imply that innovators and apps developers working in telecommunication industry have to keep ease of use and cheapness in mind when they develop products and services.

4.7 Appendix

Table 4.8 Demographic attributes of respondents

	Frequency	Percent (%)	Cumulative
Gender			
Male	324	74.48	74.48
Female	111	25.52	100.00
Country of origin			
Germany	210	43.75	43.75
Indonesia	270	56.25	100.00
Age			
Less than 20	17	3.92	3.92
20 - 30	161	37.10	41.01
31 - 40	117	26.96	67.97
41 - 50	88	20.28	88.25
Over 50	51	11.75	100.00
Education level			
Senior high school or below	88	20.32	20.32
Vocational school	106	24.48	44.80
Bachelor degree or equivalent	155	35.80	80.60
Graduate degree or higher	84	19.40	100.00
Occupation			
Employee	232	54.21	54.21
Self-employee	67	15.65	69.86
Students	53	12.38	82.24
Entrepreneur	27	6.31	88.55
Academics (teacher, lecturer, researcher)	18	4.21	92.76
Retiree	11	2.57	95.33
Unemployed	14	3.27	98.60
Other (police, nurse, etc.)	6	1.40	100.00

	Frequency	Percent (%)	Cumulative
Monthly income (nett) German respondents			
less than 1000 Euro	47	23.15	23.15
1000 - 2000 Euro	67	33.00	56.16
> 2000 - 3000 Euro	48	23.65	79.80
> 3000 - 4000 Euro	26	12.81	92.61
> 4000 - 5000 Euro	7	3.45	96.06
over 5000 Euro	8	3.94	100.00
Indonesian respondent			
less than Rp. 5 mio	74	32.31	32.31
Rp 5 mio - Rp 10 mio	77	33.62	65.94
> Rp 10 mio - Rp 20 mio	38	16.59	82.53
> Rp 20 mio - Rp 50 mio	32	13.97	96.51
over Rp 50 mio	8	3.49	100.00
Access to fixed-line telephone			
always	228	52.66	52.66
sometimes	138	31.87	84.53
never	67	15.47	100.00
Access to computer			
always	233	54.06	54.06
sometimes	156	36.19	90.26
never	42	9.74	100.00
Access to smartphone			
always	357	82.26	82.26
sometimes	53	12.21	94.47
never	24	5.53	100.00
Domestic situation			
Living with family	260	59.91	59.91
Family live in another city	144	33.18	93.09
Family live in another country	30	6.91	100.00

Table 4.9 Correlation matrix of variables for internet telephony vs. fixed-line

	1	2	3	4	5	6	7	8	9	10	11	12
1 difference in technology utility	1.00											
3 difference in image	0.61*	0.26*	1.00									
4 difference in perceived ease of use	0.59*	0.31*	0.43*	1.00								
5 difference in perceived current number of users	0.61*	0.37*	0.48*	0.64*	1.00							
6 difference in perceived future number of users	0.70*	0.50*	0.53*	0.52*	0.70*	1.00						
7 difference in perceived usefulness	0.67*	0.34*	0.52*	0.83*	0.69*	0.60*	1.00					
8 difference in attitude towards use	0.65*	0.55*	0.50*	0.66*	0.59*	0.59*	0.67*	1.00				
9 difference in subjective norms	0.67*	0.45*	0.61*	0.68*	0.71*	0.65*	0.73*	0.70*	1.00			
10 difference in perceived behavioral control	0.57*	0.22*	0.56*	0.64*	0.57*	0.48*	0.59*	0.47*	0.62*	1.00		
11 difference in intention to use	0.69*	0.49*	0.54*	0.70*	0.75*	0.71*	0.77*	0.74*	0.81*	0.57*	1.00	
12 difference in actual use	0.53*	0.34*	0.42*	0.67*	0.60*	0.54*	0.72*	0.57*	0.65*	0.50*	0.73*	1.00
Mean	1.49	2.30	0.88	0.00	1.12	2.43	0.53	0.94	0.94	0.31	1.26	0.13
SD	1.84	2.67	1.75	2.15	2.36	2.30	2.28	2.16	2.33	1.63	2.92	2.95
Min	-4.33	-5.00	-6.00	-6.00	-6.00	-5.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00
Max	6.00	6.00	6.00	5.75	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00

* $p < 0.01$

Table 4.10 Correlation matrix of variables for messaging service apps vs. fixed-line

	1	2	3	4	5	6	7	8	9	10	11	12
1 difference in technology utility	1.00											
2 difference in perceived cheapness	0.45*	1.00										
3 difference in image	0.59*	0.25*	1.00									
4 difference in perceived ease of use	0.67*	0.37*	0.49*	1.00								
5 difference in perceived current number of users	0.65*	0.40*	0.56*	0.61*	1.00							
6 difference in perceived future number of users	0.67*	0.51*	0.54*	0.53*	0.75*	1.00						
7 difference in perceived usefulness	0.75*	0.39*	0.54*	0.85*	0.67*	0.61*	1.00					
8 difference in attitude towards using	0.69*	0.56*	0.47*	0.72*	0.59*	0.58*	0.73*	1.00				
9 difference in subjective norms	0.72*	0.46*	0.61*	0.70*	0.71*	0.66*	0.76*	0.71*	1.00			
10 difference in perceived behavioral control	0.61*	0.27*	0.59*	0.65*	0.53*	0.46*	0.62*	0.50*	0.61*	1.00		
11 difference in intention to use	0.75*	0.51*	0.54*	0.72*	0.71*	0.69*	0.81*	0.77*	0.81*	0.58*	1.00	
12 difference in actual use	0.61*	0.44*	0.47*	0.71*	0.60*	0.58*	0.79*	0.68*	0.67*	0.54*	0.80*	1.00
Mean	1.58	2.55	1.00	0.36	1.83	2.79	0.65	0.98	1.21	0.50	1.51	1.30
SD	2.09	2.78	1.89	2.39	2.46	2.43	2.60	2.49	2.55	1.79	3.23	3.31
Min	-5.33	-5.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00
Max	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00

* $p < 0.01$

Table 4.11 Correlation matrix of variables for messaging service apps vs. internet telephony

	1	2	3	4	5	6	7	8	9	10	11	12
1 difference in technology utility	1.00											
2 difference in perceived cheapness	0.27*	1.00										
3 difference in image	0.45*	0.10*	1.00									
4 difference in perceived ease of use	0.49*	0.37*	0.38*	1.00								
5 difference in perceived current number of users	0.50*	0.36*	0.42*	0.55*	1.00							
6 difference in perceived future number of users	0.60*	0.26*	0.48*	0.46*	0.63*	1.00						
7 difference in perceived usefulness	0.58*	0.31*	0.40*	0.79*	0.54*	0.48*	1.00					
8 difference in attitude towards using	0.59*	0.36*	0.34*	0.63*	0.49*	0.48*	0.61*	1.00				
9 difference in subjective norms	0.56*	0.31*	0.49*	0.61*	0.65*	0.60*	0.61*	0.66*	1.00			
10 difference in perceived behavioral control	0.37*	0.35*	0.32*	0.51*	0.43*	0.32*	0.45*	0.42*	0.48*	1.00		
11 difference in intention to use	0.62*	0.40*	0.42*	0.64*	0.57*	0.52*	0.68*	0.66*	0.62*	0.54*	1.00	
12 difference in actual use	0.33*	0.30*	0.24*	0.66*	0.44*	0.34*	0.64*	0.49*	0.47*	0.41*	0.60*	1.00
Mean	0.09	0.24	0.12	0.36	0.71	0.36	0.12	0.03	0.27	0.18	0.25	1.17
SD	1.05	1.21	0.98	1.37	1.43	1.30	1.55	1.25	1.44	1.00	1.83	2.11
Min	-5.33	-5.00	-4.00	-5.50	-4.33	-4.67	-6.00	-5.00	-5.50	-3.00	-6.00	-5.50
Max	5.00	5.00	6.00	6.00	5.33	6.00	5.75	5.33	6.00	6.00	6.00	6.00

* $p < 0.01$

Table 4.12 Factor and reliability analysis for internet telephony vs. fixed-line

Factor	Item	Loading	CA
Subjective Norm	Most people who are important to me think that I should make a long-distance call with […]	0.74	0.73
	When I use […] for making a long-distance call, the people in my life whose opinions I value would...	0.49	
	Many people like me make a long-distance call with […]	0.74	
Image	Those of my friends and colleagues who use […] have more prestige than those who do not	0.72	0.79
	Those of my friends and colleagues who use […] have a high profile	0.77	
	Having and using […] is considered good style in my family, friends and colleagues	0.67	
Technology Utility	From a technical point of view, […] is a wonderful innovation in long-distance call	0.77	0.85
	In general sense, […] is a useful technology	0.74	
	From a technical point of view, […] is a valuable long-distance call	0.84	
Perceived current number of users	From my observation, the number of people today using […] is large	0.84	0.90
	Many of my friends, colleagues and family members are using […] today	0.85	
	In my opinion, many people who make long-distance call are using […] today	0.86	
Perceived future number of users	In my opinion, the number of people who will use […] in the future will be large	0.90	0.94
	Many of my friends, colleagues and family members will use […] in the future	0.90	
	In my opinion, many people who make long-distance call will use […] in the future	0.94	
Perceived usefulness	When I want to speak to my friends, family or colleagues who live in the distant places […] allows me to make a long distance call.	0.79	0.88
	[…] improves the quality of long-distance call that I make	0.75	
	Using […] for long-distance call make it easier to speak to my friends, family or colleagues in distant place	0.83	
	Overall, I find […] useful in making a long-distance call	0.82	
Perceived ease of use	Using […] for making a long-distance call is easy for me	0.77	0.84
	My interaction with […] in making a long-distance call would be	0.83	
	To make a long-distance call whenever I like, I find […]	0.60	
	For me using […] does not require a lot of mental effort	0.79	
Attitude towards using	For me to make a long-distance call using […] would be [good idea .... bad idea]	0.71	0.81
	For me to make a long-distance call using […] would be [pleasant ... unpleasant]	0.74	
	For me to make a long-distance call using […] would be [convenient ... inconvenient]	0.74	
Perceived behavioral control	To make long-distance call I have the knowledge and ability to use […]	0.63	0.57 (0.70) *
	To make a long-distance call, it is mostly up to me whether or not I use [	0.66	
	How much control do you believe you have over using […] and overcoming minor problems such as making or receiving calls, getting	0.31	
Perceived cheapness	The price per minute I pay to make long distance call by […] is ... [low .... high] - *reversed*		
Intention to use	Next time when I want to make a long-distance call, I will use […]	0.88	0.91
	Next time I make a long distance call, I plan to use […]	0.88	
Actual use	I usually use [...] when I want to make a long-distance call	0.76	0.82
	How often do you use […] in the last 30 days? [not at all .... very frequently]	0.76	

* exclusion of item 3 increase the CA score to 0.70

Table 4.13 Factor and reliability analysis for messaging service apps vs. internet telephony

Factor	Item	Loading	CA
Subjective Norm	Most people who are important to me think that I should make a long-distance call with […]	0.70	0.64 (0.77) *
	When I use […] for making a long-distance call, the people in my life whose opinions I value would...	0.35	
	Many people like me make a long-distance call with […]	0.74	
Image	Those of my friends and colleagues who use […] have more prestige than those who do not	0.77	0.83
	Those of my friends and colleagues who use […] have a high profile	0.75	
	Having and using […] is considered good style in my family, friends and colleagues	0.74	
Technology Utility	From a technical point of view, […] is a wonderful innovation in long-distance call	0.82	0.87
	In general sense, […] is a useful technology	0.79	
	From a technical point of view, […] is a valuable long-distance call device or apps.	0.81	
Perceived current number of users	From my observation, the number of people today using […] is large	0.82	0.87
	Many of my friends, colleagues and family members are using […] today	0.81	
	In my opinion, many people who make long-distance call are using […] today	0.80	
Perceived future number of users	In my opinion, the number of people who will use […] in the future will be large	0.87	0.92
	Many of my friends, colleagues and family members will use […] in the future	0.87	
	In my opinion, many people who make long-distance call will use […] in the future	0.87	
Perceived usefulness	When I want to speak to my friends, family or colleagues who live in the distant places […] allows me to make a long distance call.	0.81	0.87
	[…] improves the quality of long-distance call that I make	0.68	
	Using […] for long-distance call make it easier to speak to my friends, family or colleagues in distant place	0.82	
	Overall, I find […] useful in making a long-distance call	0.79	
Perceived ease of use	Using […] for making a long-distance call is easy for me	0.76	0.82
	My interaction with […] in making a long-distance call would be	0.80	
	To make a long-distance call whenever I like, I find […]	0.54	
	For me using […] does not require a lot of mental effort	0.77	
Attitude towards using	For me to make a long-distance call using […] would be [good idea .... bad idea]	0.73	0.79
	For me to make a long-distance call using […] would be [pleasant ... unpleasant]	0.70	
	For me to make a long-distance call using […] would be [convenient ... inconvenient]	0.71	
Perceived behavioral control	To make long-distance call I have the knowledge and ability to use […]	0.54	0.48 (0.57) **
	To make a long-distance call, it is mostly up to me whether or not I use […]	0.53	
	How much control do you believe you have over using […] and overcoming minor problems such as making or receiving calls, getting connected etc.?	0.30	
Perceived cheapness	The price per minute I pay to make long distance call by […] is ... [low .... high] - *reversed*		
Intention to use	Next time when I want to make a long-distance call, I will use […]	0.80	0.85
	Next time I make a long distance call, I plan to use […]	0.80	
Actual use	I usually use [...] when I want to make a long-distance call	0.74	0.80
	How often do you use […] in the last 30 days? [not at all .... Very frequently]	0.74	

* exclusion of item 2 increase the CA score to 0.77

** exclusion of item 3 increase the CA score to 0.57

Table 4.14 Factor and reliability analysis for messaging service apps vs. internet telephony

Factor	Item	Loading	CA
Subjective Norm	Most people who are important to me think that I should make a long-distance call with […]	0.66	0.60 (0.71)*
	When I use […] for making a long-distance call, the people in my life whose opinions I value would...	0.34	
	Many people like me make a long-distance call with […]	0.67	
Image	Those of my friends and colleagues who use […] have more prestige than those who do not	0.71	0.81
	Those of my friends and colleagues who use […] have a high profile	0.76	
	Having and using […] is considered good style in my family, friends and colleagues	0.73	
Technology Utility	From a technical point of view, […] is a wonderful innovation in long-distance call	0.83	0.86
	In general sense, […] is a useful technology	0.76	
	From a technical point of view, […] is a valuable long-distance call device or apps.	0.80	
Perceived current number of users	From my observation, the number of people today using […] is large	0.79	0.85
	Many of my friends, colleagues and family members are using […] today	0.74	
	In my opinion, many people who make long-distance call are using […] today	0.81	
Perceived future number of users	In my opinion, the number of people who will use […] in the future will be large	0.80	0.88
	Many of my friends, colleagues and family members will use […] in the future	0.84	
	In my opinion, many people who make long-distance call will use […] in the future	0.82	
Perceived usefulness	When I want to speak to my friends, family or colleagues who live in the distant places […] allows me to make a long distance call.	0.82	0.87
	[…] improves the quality of long-distance call that I make	0.72	
	Using […] for long-distance call make it easier to speak to my friends, family or colleagues in distant place	0.77	
	Overall, I find […] useful in making a long-distance call	0.81	
Perceived ease of use	Using […] for making a long-distance call is easy for me	0.77	0.81
	My interaction with […] in making a long-distance call would be	0.76	
	To make a long-distance call whenever I like, I find […]	0.57	
	For me using […] does not require a lot of mental effort	0.71	
Attitude towards using	For me to make a long-distance call using […] would be [good idea .... bad idea] - *reversed*	0.72	0.78
	For me to make a long-distance call using […] would be [pleasant ... unpleasant] - *reversed*	0.74	
	For me to make a long-distance call using […] would be [convenient ... inconvenient] - *reversed*	0.65	
Perceived behavioral control	To make long-distance call I have the knowledge and ability to use […]	0.48	0.44 (0.55) **
	To make a long-distance call, it is mostly up to me whether or not I use […]	0.49	
	How much control do you believe you have over using […] and overcoming minor problems such as making or receiving calls, getting connected etc.?	0.32	
Perceived cheapness	The price per minute I pay to make long distance call by […] is ... [low .... high] - *reversed*		
Intention to use	Next time when I want to make a long-distance call, I will use […]	0.77	0.82
	Next time I make a long distance call, I plan to use […]	0.77	
Actual use	I usually use [...] when I want to make a long-distance call	0.81	0.85
	How often do you use […] in the last 30 days? [not at all .... Very frequently]	0.81	

* exclusion of item 2 increase the CA score to 0.71

** exclusion of item 3 increase the CA score to 0.55

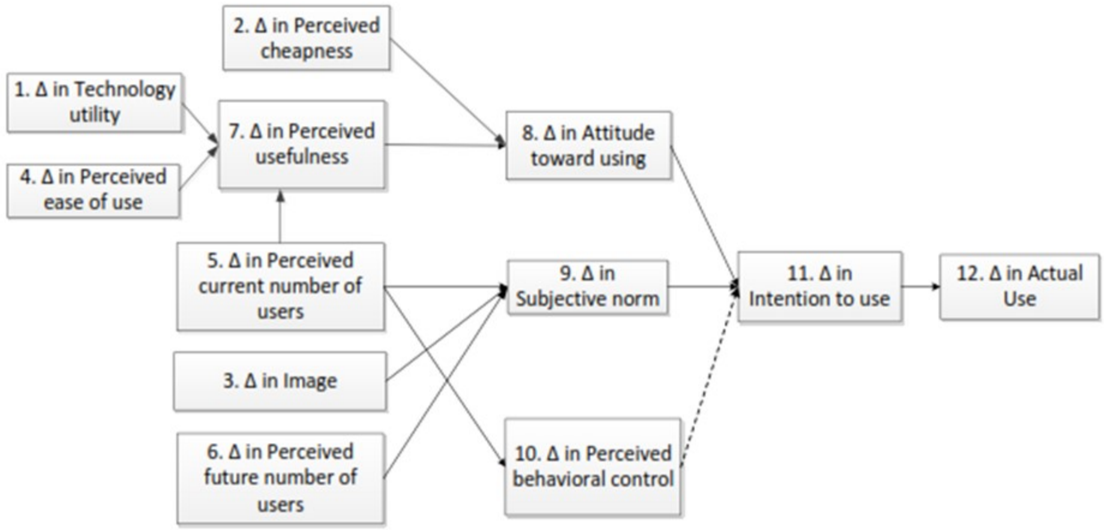

Figure 4.3 Structural diagram of internet telephony vs. fixed-line

----- means that the relationship is not significant

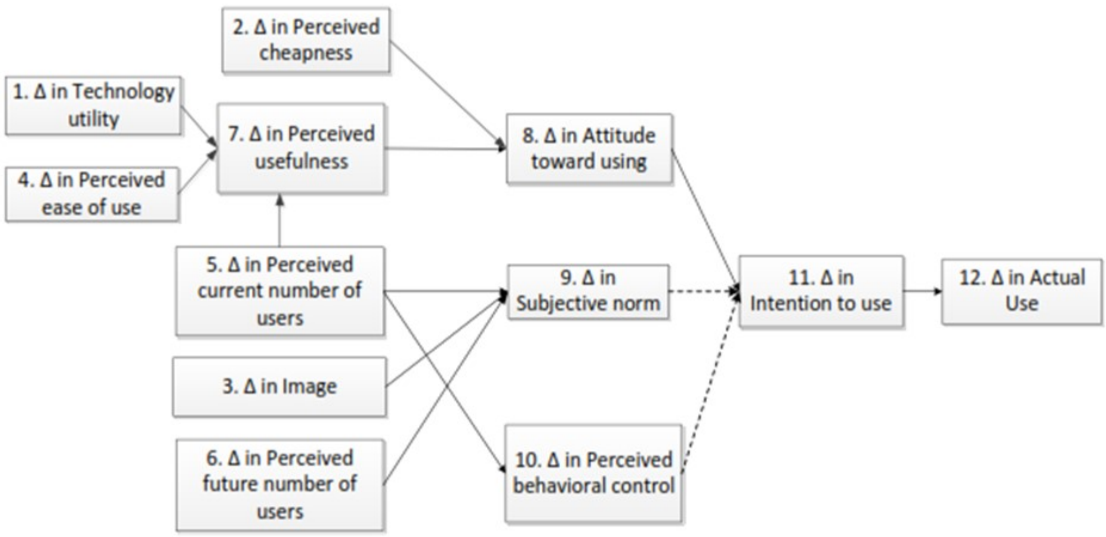

Figure 4.4 Structural diagram of messaging-service apps vs. fixed-line

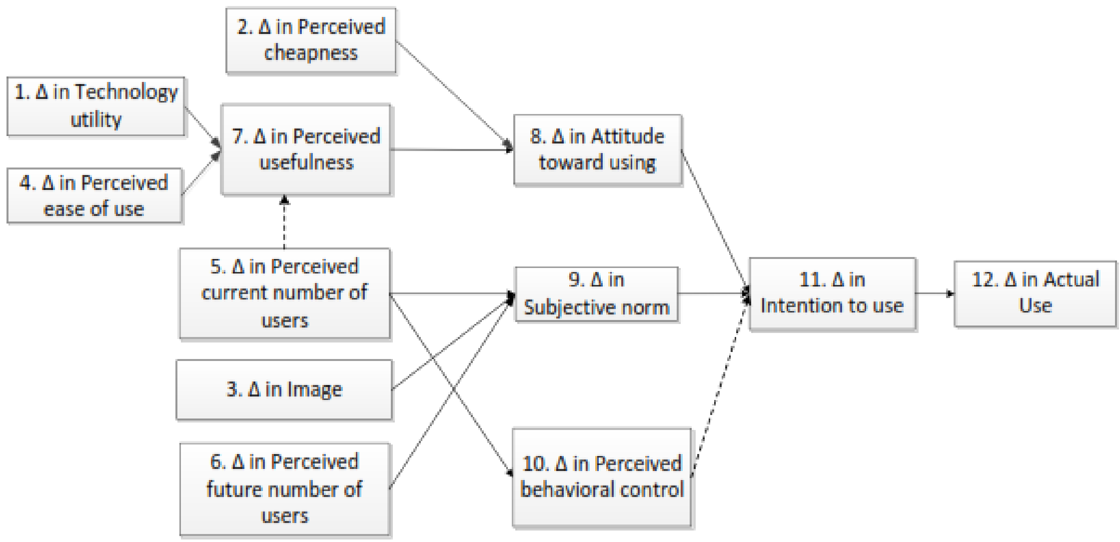

Figure 4.5 Structural diagram of messaging-service apps vs. internet telephony

5 Conclusion

This thesis aims to address the following issues:

1. How do network effects influence the mechanism of disruptive technology and the probability of technology disruption (Chapter 2)?
2. How do consumer network structures play a role in the probability of technology disruption (Chapter 3)?
3. What are the determinants of user acceptance of disruptive technology characterized by network effects (Chapter 4)?

This chapter summarizes the findings of the thesis in Section 5.1, highlights the novelty of the study in Section 5.2, explains the theoretical, managerial, and policy implications in Section 5.3, and identifies the limitations in Section 5.4

5.1 Overview of the main findings

5.1.1 The influence of network effects on the mechanism of disruptive technology and the probability of technology disruption

Although many modern technologies are characterized by network effects, existing models of disruptive technology lack formalization of these. This chapter attempts to address this shortfall and proposes the following hypotheses:

> *Hypothesis 1:* The dynamics and outcome of disruption are affected by the interplay between technological development, consumer choice, Firm decisions and demand structure.

The first hypothesis is addressed in this chapter by incorporating companies' technology development, companies' allocation and actions in product and process innovation, consumer decisions, and the structure of demand in the model and simulation. The simulation was conducted to show the interaction between companies and consumers in the market segments and interplays between market segment preferences and different degrees of network effects.

> *Hypothesis 2:* The strength of network effects influences the probability of disruptive innovation as one of the competitive outcomes.

The second hypothesis is tested by a simulation whose results showed that weak or low level network effects allow different competitive regimes, i.e. competitive isolation, convergence or disruption, to occur.

Within the context of this investigation, multi-segment markets signify those consisting of mainstream and niche segments. Multi-segment markets with homogeneous preferences emerge when the consumers in a mainstream segment demonstrate a uniform preference for certain product technology characteristics. In contrast, consumers in niche segments also harbor a uniform preference, albeit towards different characteristics. Multi-segment markets with homogeneous preferences in weak network effects situation facilitate competitive isolation outcomes.

The simulation result shows that only when a network effect is weak might competitive isolation occur. Competitive isolation suggests that consumers in a mainstream market adopt product technology with certain characteristics, whereas those in niche markets adopt product technology with other characteristics. From a supply-side perspective, Firm 1 operates in mainstream segment, while Firm 2 is active in isolation within a niche segment. However, in the market demonstrating homogeneous preferences and strong network effects, monopoly occurs. Firm 1 dominates both the mainstream and niche segments. This situation is similar to Arthur's model where the winner takes all.

Heterogeneity in consumer preferences matters and influences competitive outcomes. The term 'heterogeneous preferences situation' refers to one in which consumers in the mainstream segment hold different preferences, i.e. a number of them show a preference for Characteristic 1 (mainstream), while some of them harbour one towards Characteristic 2 (alternative). Markets containing heterogeneous preferences and weak network effects allow competitive convergence and competitive disruption to occur. Competitive convergence occurs when Firm 1 and Firm 2 co-exist and operate within the mainstream segment. This result confirms the notion of the diverse preferences that allow new companies with innovative technology to survive as argued by Malerba, et al. (2007).

At some point, when consumers in the mainstream segment whose preferences for Functional Characteristic 2 (alternative) is larger than Characteristic 1 (mainstream), competitive disruption might occur in the market within a heterogeneous preferences and weak network effects scenario. The theory of disruptive technology provides a changing preference mechanism through the notion of diminishing consumer marginal utility, due to performance oversupply of established technology (Adner 2002; Christensen,1997). In the literature, the changing preferences of consumers can also be identified from research into psychology and, recently, economists have discussed the relevance of preference change to economic research (Bowles, 1998; Janssen and Jager, 2001; Witt, 1991).

The situation of strong network effects, however, leads again to a monopoly regardless of the heterogeneity of consumer preferences. Strong network effects always lead to winner-takes-all and eventual lock-in situations.

5.1.2 Competition and technology disruption in social networks

This chapter seeks to present a theoretical contribution by addressing the gap in the literature on disruptive technology and network effects, i.e. incorporating consumer network structures and proposing a line of argument as to how network structures influence the probability of disruption. The core question is as follows: how do consumer network structures influence the probability of technology disruption, particularly in the presence of network effects? The better we understand consumer network structure and its influence on the probability of disruption, even when strong network effects are present, the greater the potential contribution to the discourse about overcoming lock-in by support for Witt's notion of critical mass formation.

Drawing on the literature concerning the diffusion of innovation, technology competition and complex networks, the author understands that the influence of consumer network structures on market dynamics and competitive outcome cannot be ignored. Omitting such structures from the technology competition model might be misleading, especially when network effects are present, in terms of overemphasizing the installed base. This chapter provides a 'map' of the probability of technology disruption in different consumer network structures.

Regarding the question of how consumer network structures influence the probability of technology disruption, a specific conjecture is proposed in this chapter. Its premise is that a new, potentially disruptive technology has a better chance of survival in a market characterized by high clustering and long path length, since these network characteristics are favorable to incompatible entry and to entrants forming a niche. The consumer network structure characterized by regular topology, or small-world topology with few shortcuts, can provide a favorable condition for a new, potentially disruptive technology. Once this technology gains a foothold in the niche, new entrants or companies should invest effort in forming new shortcuts or 'diffusing actors' to spread the information as well as coordinate its adoption (Witt, 1997) in an attempt to enter a mainstream segment. If this step is not taken, the new technology will remain isolated in niche. This attempt, coupled with performance oversupply of established technology, might yield critical mass and increase the probability of disruption.

5.1.3 Acceptance of disruptive technology with network effects: an empirical study of long distance calls in Germany and Indonesia

This chapter seeks to shed light on how technology disruptiveness and network effects play a role in consumer acceptance. In this empirical study, 480 responses from the general public in Germany and Indonesia have collected to investigate consumeracceptance of three different technologies: fixed-line telephone, internet telephony, e.g. Skype, and messaging-service apps, for example, WhatsApp. The final dependent variable is the difference in actual use between technologies and the model is based on the Theory of Planned Behavior and Technology Acceptance Model combined with several variables related to network effect.

From the data collected on the three different product technologies, comparisons between two of the technologies were made by taking the difference in the mean value of every variable. This study investigated three cases of multiple regression based on comparisons between technologies, i.e. (1) internet telephony vs. fixed line, (2) messaging service apps vs. fixed line and (3) messaging service apps vs. internet telephony. Every case consisted of twelve variables (Table X). The relationships between variables are illustrated in Figure 10.

Table 5.1 Names and abbreviations of variables

	Variable name	**Abbreviation**
1	Difference (Δ) in Technology Utility	dTUTIL
2	Difference (Δ) in Perceived Affordability	dPCHEAP
3	Difference (Δ) in Image	dIMAGE
4	Difference (Δ) in Perceived Ease of Use	dPEoUSE
5	Difference (Δ) in Perceived Current Number of Users	dPCUSER
6	Difference (Δ) in Perceived Future Number of Users	dPFUSER
7	Difference (Δ) in Perceived Usefulness	dPUSEFUL
8	Difference (Δ) in Attitude Towards Using	dATU
9	Difference (Δ) in Subjective Norm	dSNORM
10	Difference (Δ) in Perceived Behavioral Control	dPBCONT
11	Difference (Δ) in Intention to Use	dINTENT
12	Difference (Δ) in Actual Use	dACTUAL

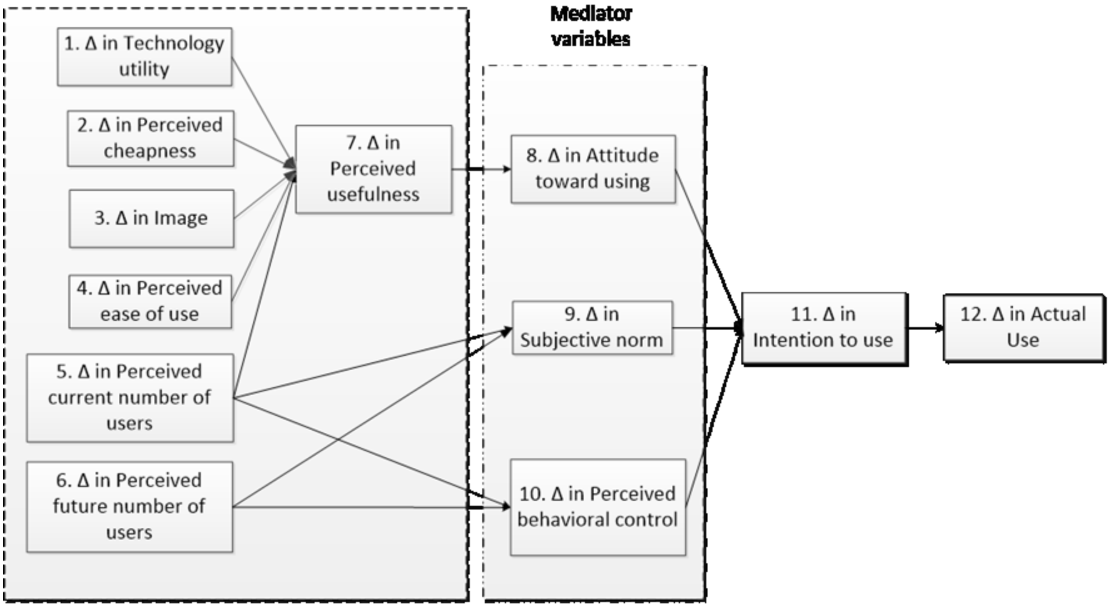

Figure 5.1 Proposed model to investigate the acceptance of disruptive technologies with network effects

In all three cases, dINTENT are positively and significantly related to dACTUAL. These results are consistent for all three cases and, hence, provide support for TAM and TPB frameworks. The mediation effect of the difference of dATU on the positive effect of dPUSEFUL towards dINTENT is shown in all three cases, albeit to varying degrees. For example, with internet telephony vs. fixed-line and messaging-service apps vs. internet telephony, it is dPEoUSE which explains dPUSEFUL most clearly. However, in the case of messaging-service apps vs. fixed-lines, it is dPCUSER which exerts the largest impact on dPUSEFUL.

The mediation effect of dSNORM is supported by the data in the case of internet telephony vs. fixed line and messaging-service app vs. internet telephony. However, this does not apply to the messaging-service apps vs. fixed-line telephone comparison, due to an insignificant relationship between dSNORM and dINTENT. This result suggests that the difference in intention to use WhatsApp over fixed-line telephones is mainly influenced by differences in the perceived current number of users (which has an indirect relationship with dINTENT), rather than social pressure from other people or groups.

The mediation effect of dPBCONT is consistently absent in all three cases since dPBCONT is not significantly related to dINTENT. The possible explanation for this situation is that making long-distance calls and operating telecommunication devices such as fixed-line telephones, Skype or a messaging-service app is a straightforward task requiring extremely limited control or effort to perform. It might also be the case that perceived behavioral control becomes less relevant.

In addition, the findings confirmed that dIMAGE is not significantly related to dPUSEFUL as hypothesized but, instead, is positively and significantly related to dSNORM in allcases. With regard to the network effects-related variable dPFUSER, the results are mixed. In the case of internet telephony vs. fixed-line telephones, dPFUSER is positively and significantly related to dSNORM, but not to dPBCONT. Subsequently, dSNORM is positively and significantly related to dINTENT. Therefore, dPFUSER is indirectly related to dINTENT through dSNORM. Whereas in the case of messaging-service vs. fixed-line, dPFUSER is positively and significantly related to dSNORM but dSNORM is not significantly related to dINTENT. Hence, dPFUSER is not related, even indirectly, to dINTENT. The case of messaging-service apps vs. internet telephony showed that dPFUSER is indirectly related to dINTENT through dSNO.

Surprisingly, the German data showed that the mean of actual use of fixed-line is higher than that of internet telephony and messaging-service apps, despite the global trend of disruption in long-distance calls. It might tentatively indicate that, for long-distance calls, Germans are locked into fixed-line telephone use.

5.2 Novelty

Following a careful review of several studies incorporating a formal model of disruptive technology mechanism, the lack of an explicit formulation of the influence of network effects on such models was identified. The novelty of this study lies in the incorporation of network effects into the formalization of technology disruption mechanism, where the heterogeneity of consumer preferences and minimum requirements are taken into account (Chapter 2). The evidence of how strong network effects prevent technology disruption is not new. Nevertheless, the results highlighting the heterogeneity of consumers preferences and its role in shaping competitive outcomes when network effects are weaker might represent a novel insight (Chapter 2).

One strong assumption underlying technology competition between network effects is that every individual consumer is connected to every other member of the population or the assumption of a complete network. This assumption leads to a lock-in outcome, while, in reality, competing technologies coexisting in the market can be observed. Considering that consumer decisions relating to technology adoption might be more influenced by a limited number of significant others, such as friends, colleagues, or family members, the complete network assumption needs to be relaxed by considering different consumer network structures within social networks. Therefore, this study tries to fill that gap by discussing and mapping the competition dynamics and disruptive technology in social networks into a framework of thought. Moreover, it elaborates how different consumer network structures influence the probability of technology disruption. Incorporating consumer network structures into the discourse of disruptive technology and the likelihood of technology disruption is novel (Chapter 3).

Chapter 4 contains empirical research that is novel from a number of perspectives. Firstly, different technologies characterized by the disruptiveness and network effects are assessed. Conceptually, disruptive technology theory, put forward by Christensen (1997), and network effects or network externalities theory a la Arthur (1989) are referred to. Secondlyunlike most empirical studies of technology acceptance which investigate single technologies or innovation, e.g. the adoption of internet banking (Lee, 2009; Amin, 2009; Pikkarainen et al., 2004), mobile phone payments (Chen, 2008), instant-messaging service (Wang et al, 2005), in this study three different technologies, albeit ones in the same category, are assessed. Thirdly, as the fundamental behavioral model guiding our research, the theory of planned behavior (TPB) (Ajzen, 1991) properly extended to a model of technology adoption (TAM) (e.g. Davis et al., 1989) has been applied. Fourthly, instead of investigating the factors of technology acceptance independently, regression variables are formulated in a comparative manner, e.g. contrasts in actual use between internet and fixed-line telephony, differences in intention to use between messaging-service apps and fixed-line system.

5.3 Implications

An enhanced understanding of how consumer network structures influence the probability of technology disruption could have policy implications. Ignoring their role in assessing technology competition and the likelihood of technology disruption might result in overemphasizing the installed base. This was the case in the US when the FCC issued a regulation to prevent AOL from adding certain features in order to prevent the establishing of a monopoly in the area of instant messaging. To ensure an equitable policy on and regulation of technology competition, government bodies should take into account not only network effects, but also consumer network structures. The results of this study have potential implications for disruptive technology theory by emphasizing the importance of consumer network structures in potential technology disruption as well as by showing how the varying degrees of network effects influence the mechanism of disruptive technology.

In Chapter 4, the results confirm that network effects influence the acceptance of new technology over established varieties in one of two ways: (1) subjective norms or social pressure from peer groups and close associates and/or (2) perceived current and future numbers of users as representatives of an established base, albeit to different degrees. Since differences in the perceived user numbers have an indirect but positive and significant effect on the variations in intention to use, it is important for providers or developers of internet telephony services, not to mention messaging-service apps, to launch a strategy the purpose of which is intended to create, in the short term, a large solid base. Particularly in developing countries, where fixed-line telecommunication infrastructure is relatively under-developed and fixed-line services are not widely available or are relatively expensive, internet telephony and messaging-service apps or internet and mobile applications, in general, might enjoy a greater potential for acceptance and use by the mainstream. Advancements in internet and mobile technology, people's alacrity in accepting the internet and mobile apps as well as a favorable social network structure can be seen as representing an opportunity for the Indonesian government to provide telecommunications access to people by accelerating the provision of mobile telecommunication infrastructure.

5.4 Limitations

The results of this study are certainly not free from certain limitations which can result from assumptions used in the model and simulations as well as the methodological issues in the empirical study. The underlying assumption of the model contained in Chapter 2 is that any individual consumer is connected to every other counterpart in the population. This, of course, represents a powerful assumption since we observe that, in reality, any decision taken by an individual might be influenced only by his/her local network, e.g. family, friends or work colleagues. It has also been assumed that consumers possess perfect knowledge when evaluating product characteristics. This must also constitute a strong assumption because consumers often do not have such knowledge of product characteristics. Reasons for imperfect consumer knowledge could be that individuals have limited access to information, lack the time to conduct proper research or are merely being lazy because they consider it not to be worth the effort (Valente, 2012). Another limitation is the lack of empirical validation for this study.

The assumption of complete networks present in Chapter 2 does not apply to Chapter 3 where consumer network structures are taken into account. The qualitative and intuitive nature of theoretical exercise contained in this paper, however, requires formalization into a mathematical model which could constitute a challenging but exciting task for a future research project. Furthermore, an agent-based model and simulation might also represent a viable option to formalize the abstraction presented in this chapter. The theoretical nature of this chapter also requires empirical evidence to support the proposed theory of technology disruption in social networks.

The empirical study in Chapter 4 is cross-sectional in nature with the result that the findings form a limited causal interpretation. Since a particular type of product technology, i.e. that necessary for long-distance calls, was investigated, caution should be exercised in not generalizing the results of this study to include product technologies with distinct characteristics. Moreover, since the research reported here was conducted in German and Indonesian contexts, the extent to which its results can be generalized to other countries is limited.

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Curriculum Vitae

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Sex Male | *Date of birth* 21/08/1972
Nationality Indonesian

Work Experience

Sept. 2011 – Oct. 2013

Faculty Member
School of Business and Management, Bandung Institute of Technology, Indonesia

- Teaching: Management of Technology, Business Venturing, Innovation Management to master and bachelor students.
- Conducting research on management of innovation, acceptance of disruptive technology.

Sept. 2009 – Oct. 2010

Innovation Consultant and Project Assistant
Wavin Technology and Innovation, BV, The Netherlands

- Dealing with front-end of Wavin's new product development process.
- Providing consultation on improving the overall product innovation workflow and on supportive management tools, specifically newness and complexity map frameworks and scoring systems to improve market orientation and speed.

Aug 1999 – Aug 2008

Head of Research and Development
PT. Indoneptune Net Manufacturing, Indonesia

- Managing new product development projects: eco-friendly and fuel-saving set net in South Sulawesi, Indonesia
- Managing product development of assembly net for Russian market and fast-mounting fishing net for French market.

Education

Oct 2013 – to date

Doctoral candidate
Friedrich-Schiller-Universität Jena, Germany

- Carrying out empirical research, collecting primary data through survey in Germany and Indonesia and conducting data analysis with Stata. Have experiences also analysing data using SPSS (Amos) and R.

- Conducting theoretical study on technology competition, competitive diffusion, disruptive technology or innovation & network effects by employing agent-based modelling and simulation using programming software of Laboratory for Simulation Development (Lsd).
- Conceptualizing competitive diffusion and disruptive innovation in a complex network, employing social network analysis.

Oct 2008 – Dec. 2009 Master of Business Administration

1. Nyenrode Business University, The Netherlands
2. Kellogg School of Management, Northwestern University, USA
   - General management with thesis on innovation management.
   - Thesis: build a solid upfront stage in New Product Development: Composite Manifold case in Wavin, NV, Netherlands.

Aug. 1991 – Apr. 1997 Bachelor in Engineering Physics

Bandung Institute of Technology, Indonesia

- Specialization in instrumentation and control
- Bachelor thesis on PID evaporator controller in chemical processing

Awards

- DAAD Research Grants for Doctoral Candidates and Young Academics and Scientist, 2013 - 2017
- Cedo-Nulli (Nyenrode) Scholarship for Indonesian Talent, 2008- 2009
- Won the Global Collect Business Game in Brand Awareness and Online Reputation (Nyenrode) - 2009
- Won the 7th YWCA – YMCA Japanese Speech Contest – 2003

Language

Indonesian : mother tongue
English : fluent (IELTS score: 7.5, C2)
Japanese : fluent (Nihongo Noryokushiken level 2, C1)
German : intermediate (B1)